MARKETING STRATEGIES IN THE PRESENCE OF EXTERNALITIES

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Lay Abstract

Externalities are pervasive in daily life and affect businesses' strategic marketing decisions across various contexts. These externalities arise from various sources—market interactions, firm strategies, and consumer behavior—yet they are often neglected in marketing decision-making. Overlooking these externalities may result in suboptimal marketing performance. Despite their importance, there remains a limited understanding of how externalities shape marketing decisions and business outcomes.

This dissertation investigates how externalities affect marketing strategies from three perspectives: between two marketplaces, within firms' strategies, and among consumers. Using analytical models and empirical methods, I examine the impact of different externalities on pricing strategies in the platform economy, timing strategies in livestream shopping, and brand-influencer collaborations. The findings broaden the existing theory and offer valuable managerial insights for platforms, influencers, and brands, advancing our understanding of externalities and their implications for marketing strategies.

Abstract

Externalities arise when an economic agent's activities generate side effects on the activities, welfare, or outcomes of other agents, or even the agent itself. Their impact on marketing strategies is inevitable, and overlooking these externalities may lead businesses to miss key factors and valuable opportunities. Although a substantial body of literature in economics and marketing has examined various externalities, the definitions of the concept and implications for marketing strategies vary. Furthermore, extant literature on the platform economy has primarily focused on externalities within the marketplace, while few studies have examined various externalities in livestream shopping and influencer marketing. This dissertation addresses these gaps.

Chapter 1 expands the definition of externalities and synthesizes the relevant literature on how common externalities affect marketing strategies from three perspectives: marketplaces, firms, and consumers. Chapters 2 through 4 are each positioned within these perspectives, examining the marketing applications of externalities across different contexts.

Chapter 2 examines cross-platform network externalities, the externalities between two marketplaces in the platform economy. Existing studies have focused on cross-side network externalities between buyers and sellers within a single marketplace. My study highlights that multi-homing users—those who use multiple platforms—connect the economies on these platforms by interacting with other users through cross-side network externalities within these platforms. Consequently, cross-platform network externalities arise when two platforms share a sufficient number of multi-homing users. Using an analytical model, I illustrate and quantify the formation of cross-platform network externalities and their impact on platform pricing decisions.

Chapter 3 studies two externalities in livestream shopping, a new business model that offers interactive, entertaining, and real-time online shopping experiences. In this context, influencers

can schedule their shows at any time to engage with their audience. One type of externality that affects their timing decisions is scheduling consistency, which refers to the effects of the influencers' previous show dates on the timing of the current one. Another type is the externality exerted by other influencers streaming simultaneously with the focal influencer. Using a comprehensive dataset. I empirically investigate how these two externalities affect influencers' timing decisions in livestream shopping.

Chapter 4 explores two types of externalities in influencer marketing, where brands incentivize influencers to promote their products or services. In this brand-influencer collaboration, an externality arises when brands' actions generate a side effect on the influencers. For example, a brand's established awareness may enhance the influencer's popularity. In addition, externalities exist among the influencers' audience, as one audience's purchases may influence other audiences' purchasing decisions. Analytical models are used to examine how these externalities affect brand influencer collaboration strategies.

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It takes a whole family to raise a Ph.D.

Dedicated with heartfelt gratitude to my family and extended family.

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1. Externalities

Externalities are pervasive in our daily lives, in activities that involve multiple parties or multiple transactions. For example, in a residential community, a well-maintained lawn by one household creates a positive externality to its neighbors, enhancing the neighborhood's aesthetics and potentially increasing the property value. At events like concerts or cinema shows, noise from the audience leads to a negative externality, disrupting the experiences of others.

Similarly, in businesses, diverse externalities may affect a firm's strategic marketing decisions. A substantial body of literature in economics and marketing has examined various externalities, including information externalities (Hendricks & Kovenock, 1989), housing externalities (Autor et al., 2014; Rossi-Hansberg et al., 2010; Rossi-Hansberg & Sarte, 2012), advertising externalities(Anderson & Simester, 2013; Sahni, 2016), brand externalities (Balachander & Ghose, 2003; Deng et al., 2022), audience externalities(Wilbur et al., 2013), marketing avoidance externalities(Goh et al., 2015; Hann et al., 2008), and network externalities (Armstrong, 2006; Rochet & Tirole, 2006). These externalities can be either positive or negative. Positive externalities enhance business outcomes, whereas negative externalities result in adverse effects. Ignoring these externalities may lead to suboptimal marketing decisions, causing firms to miss the potential benefits or drawbacks from externalities, overlook the true value of their products or services, or misalign with consumer needs and preferences.

However, despite the extensive body of research, the definitions of externalities and their implications on marketing strategies vary across contexts. This chapter synthesizes the definitions of externalities and summarizes the externalities associated with marketing activities from three perspectives: marketplaces, firms, and consumers, and positions each of the subsequent chapters within this framework.

1.1. Definitions of Externality

The concept of externality was first introduced by Pigou (1920), who used environmental pollution as an illustrative example. He demonstrates that certain firms' production processes could generate pollution, leading to a negative externality that harms society. To address this issue, Pigou (1920) advocates government intervention through corrective taxes. This approach reflects his concern with the effects of externalities on social welfare. Building on this foundation, Tirole (1988) has expanded the concept to include economic agents involved in production and consumption, defining an externality as: "*An externality arises when the consumption of a good by a consumer directly affects the welfare of another consumer, or when a firm's production affects other economic agents.*"

In the same vein, Mas-Colell et al. (1995) have defined externality as follows. "*An externality is present whenever the well-being of a consumer or the production possibilities of a firm are directly affected by the actions of another agent in the economy.*" They emphasize the term "directly" to "exclude any effects that are mediated by prices"[1]. To illustrate this, they provide the example of a fishery's productivity being impacted by emissions from a nearby oil refinery, highlighting how an externality arises.

The previous definitions suggest that externalities arise when multiple economic agents are involved, typically impacting social welfare or public goods. However, externalities can also emerge within a firm's own business activities. A substantial body of literature on umbrella branding explores the externalities between child and parent brands (Aaker & Keller, 1990; Balachander & Ghose, 2003; Hennig-Thurau et al., 2009; Ishihara et al., 2022; John et al., 1998),

[1] The externality that can be mediated by prices is defined as "pecuniary externality" by the economist Jacob Viner (1931). Mos-Colell, Whinston and Green (1995) state that a pecuniary externality is present when the fishery's profitability is affected by the price of the oil (which may be affected by the output of oil refinery's output).

demonstrating that externalities can exist within a single firm's activities. Externalities may also arise between a firm's product categories (Erdem & Sun, 2002) or across different strategies (Rutz & Bucklin, 2011; Yang & Ghose, 2010). Therefore, rather than limiting the concept of externality to social welfare or public goods, I adopt a broader approach that incorporates the impact of various externalities within firms' strategic marketing decisions. Thus, I define externality as:

"An externality is present when an economic agent's activities generate secondary effects on the activities, welfare, or other aspects of other agents, or result in self-imposed spillovers that are not fully internalized by the same agent. The impacts mediated via pricing mechanism are often referred to as pecuniary externalities, but not the real externalities."

Furthermore, research has used the terms "externalities" and "spillover effects" interchangeably (Chae et al., 2017; Kriejestorac et al., 2020; Liang et al., 2019; McGranaghan et al., 2019; Pattabhiramaiah et al., 2019; Peres & Van de Bulte, 2014; Syam & Pazgal, 2013; Thomas, 2020). In this thesis, these terms will be used interchangeably based on the context.

1.2. Externalities Related to Marketing Strategies

A rich body of literature has explored various externalities and their implications for marketing strategies. This subsection provides an overview of the literature from three perspectives: marketplaces, firms, and consumers, with a detailed summary presented in Table 1.1.

1.2.1. Externalities From Marketplaces' Perspective

1.2.1.a. Network externalities within a marketplace

A two-sided marketplace (i.e., platform), such as Uber, Airbnb, or Instacart, connects buyers and sellers to facilitate transactions. A key feature of these platforms is network externality, which refers to the marginal benefit of users on one side to the users on the other side (Armstrong, 2006). As the number of buyers increases, more sellers are drawn to the platform, and vice versa. This overall impact of network externality is known as network effects.

Although network externalities and network effects are inherent to two-sided marketplaces, these concepts are borrowed originally from the literature on networks. Katz and Shapiro (1985) first defined network externalities in a one-side market as "the utility that a given user derives from the goods depends upon the number of other users who are in the same network." This is also referred to as direct network externalities, which arise when the product is valued on the number of users who use the same product on the same side of the marketplace (Katz & Shapiro,1985; Rysman, 2019). A common example is communication networks; telephone users' utility increases when more consumers use the services. In contrast, indirect network externalities are present when one user's adoption of a product has no direct but lagged effects through other complementary products (Farrell & Saloner, 1985; Katz & Shapiro, 1994). For example, the provision of software can indirectly affect hardware adoption.

Building on these definitions, Armstrong (2006) and Rochet and Tirole (2003) introduce the network externality and network effects to a two-sided marketplace. In a two-sided marketplace, network externality[2] is indirect, as the benefit of users on one side of the marketplace depends on the number of users on the other side. Although "network externality" and "network effects" are used interchangeably in the literature, network externalities refer to the one-way impact from one side to the other side, while network effects are the overall impacts of the network externalities. Several scholars have examined platform pricing in the presence of network externalities and network effects (Armstrong, 2006; Hagiu, 2006, 2009; Rochet & Tirole, 2003, 2006). The major finding is that the platform subsidizes the users on the side of the marketplace when network

[2] This is also referred to as cross-side network externality.

externalities are present. For example, Airbnb provides free services to travelers while charging fees to hosts, and Google Play charges developers to launch applications while offering free downloads to consumers.

1.2.1.b. Network externalities between marketplaces

Extant literature has focused on the network externalities within a two-sided marketplace. However, as more platforms emerge, an increasing number of users may use multiple platforms (i.e., multi-homing users). Therefore, these platforms may be "connected" when they share a substantial group of multi-homing users. Hence, cross-platform network externalities arise because of the multi-homing users. Chapter 2 of this thesis defines cross-platform network externalities and examines their implications on pricing strategies.

1.2.2. Externalities From Firms' Perspective

Activities within and across firms, including those brands and influencers, generate various externalities. In this subsection, I summarize the literature on externalities from the firm's perspective, focusing on three key dimensions: within a firm's activities, among peers, and between business partners.

1.2.2.a. Externalities within a firm's activities

Firms benefit from positive externalities across different product categories, outlets, and strategies within the same firm. Erdem and Sun (2002) find that advertising in one category exerts positive spillover effects on other categories in the same brand. Similarly, Unnava and Aravindakshan (2021) demonstrate that brands can improve customer engagement when posting across different social media platforms. Kriejestorac et al. (2020) show that a video's viewership on one social media platform may be increased by firms' subsequent posts of the same video on a new platform. In online advertising, firms benefit from positive spillover effects between organic advertising and sponsored search advertising (Yang & Ghose, 2010), between search ads and display ads from the same firm (Kireyev et al., 2015), and between bidding on generic and branded keywords (Rutz & Bucklin, 2011).

However, externalities that arise between extended and parent brands are two-way and can be positive or negative. On the one hand, advertising of the parent brand may boost the sales of a new brand, creating positive forward spillover effects (Balachander & Ghose, 2003; Hennig-Thurau et al., 2009). Similarly, advertising a new brand may positively impact the existing brand, resulting in reciprocal spillover effects (Aaker & Keller, 1990; Balachander & Ghose, 2003; Hennig-Thurau et al., 2009). On the other hand, brand extensions can dilute the parent brand as there is a lack of consistency between the extension and the established brand, leading to negative spillover effects (John et al., 1998). In addition, introducing limited-time new products can increase overall brand demand but reduce sales of the parent product (Ishihara et al., 2022).

Chapter 3 of this thesis examines the externality within an influencer's activities in livestream shopping.

1.2.2.b. Externalities among peers

Externalities may arise when a firm's activities generate positive or negative impacts on the welfare or activities of its peers. Advertising can create positive externalities to the sales of competing retailers (Anderson & Simester, 2013). For example, consumers may receive pre-sale information (e.g., test drives or salespeople demonstrations) or advertisements from one retailer but ultimately purchase the product or services from other retailers (Tirole, 1988). Similarly, online ads for restaurants may increase the chances of sales for non-advertised restaurants, particularly those that serve cuisine similar to that of the focal restaurants (Sahni, 2016). The same impact is observed in television advertisements of prescription antidepressants, which can influence the demand for rivals' products (Shapiro, 2018). In contrast, advertising e-cigarettes reduce the demand for traditional cigarette and smoking cessation products (Tuchman, 2019). Negative externalities may also arise among TV within the same break (Wilbur et al., 2013), as well as when a firm is involved in controversial practices, such as data breaches (Kashmiri et al., 2016) or scandals (Roehm & Tybout, 2006).

The impact of externalities among peers can be complex. In the platform context, a platform-recommended featured app may exert overall positive spillover effects on other mobile applications. However, the extent of these effects depends on the specific relationship between the featured and non-featured apps (Liang et al., 2019). Similarly, the spillover effects from the firm filing for bankruptcy may increase the demand for products from other firms in the same industry. However, these effects may also be negative, as the bankruptcy of the focal firm raises consumer uncertainty, leading to reduced demand (Ozturk et al., 2019).

Chapter 3 of this thesis also examines the externalities among the influencers with different follower count and their implications on influencers' timing strategies.

1.2.2.c. Externalities between business partners

Some studies have explored the externalities among business partnerships. When a focal firm collaborates with multiple agents, advertising investment by one partner can affect the business outcomes of the other partners (Chennamaneni & Desiraju, 2011). In joint product development, positive spillover effects from one partner to others may lead to underinvestment problems (Amaldoss et al., 2000). Similarly, in R&D alliances, the externality among the partners may result in lower R&D investments (Veugelers, 1998). In addition, how a brand is perceived by consumers exerts spillover effects on other brand alliances (Simonin & Ruth, 1998). Externalities may also exist in vertical partnerships, where the digital transformation of a focal firm incentivizes upstream and downstream partners to pursue their own digital transformation (Geng et al., 2024).

Chapter 4 studies the externality between the brand and the influencer in the context of influencer marketing.

1.2.3. Externalities From Consumers' Perspective

Externalities arise when one consumer's actions generate side effects to the welfare or activities of other consumers. An example of such externalities is the marketing avoidance externality, which refers to the impact of consumers' avoidance of solicitations on other consumers (Hann et al., 2008). When some consumers conceal from direct marketing by registering on the "Do Not Call" list, they generate a negative externality to other consumers who do not register on the "Do Not Call" list, as the remaining consumers receive more calls from the telemarketers marketing (Goh et al., 2015). Another example of externalities among consumers is between informed and uninformed consumers. When the consumers are informed about the products or services offered by the firms, they exert a positive externality on the uninformed consumers because the informed customers are demanding and will drive up the product/service quality (Tirole, 1988). Besides, informed consumers also benefit from the presence of uninformed consumers as the uninformed consumers contribute to extra revenue that may be passed back to all the consumers (Armstrong, 2015).

Externalities arise in word-of-mouth communication among consumers. For example, when firms offer a referral program or a free contract, consumers who have experienced a product or service are encouraged to share their experiences with others, creating positive externalities by influencing others' decisions (Kamada & Ory, 2020). Additionally, firms may also strategically select certain consumers as seeded customers and encourage them to spread information through word-of-mouth to non-seeded consumers. Although these seeded customers may generate positive spillover effects to non-seeded consumers at the product level, they may also negatively impact related products at brand and category levels (Chae et al., 2017). Furthermore, consumers' online reviews of one product may positively or negatively affect other consumers' purchasing decisions of related products, depending on product characteristics and reviewers' experiences (Kwark et al., 2021). Negative online reviews posted by consumers may reduce the likelihood that other consumers will purchase the same product, resulting in negative externalities among consumers (Varga & Albuquerque, 2024). Furthermore, online ratings and popularity based on past consumer behavior can influence purchasing choices. For example, online ratings or popularity based on consumers' past purchase history may also create externalities. Consumers' purchase choices may be affected by the vendors' popularity based on other consumers' activities (Tucker & Zhang, 2011), and prior online ratings may affect the users' ratings (Lee et al., 2015).

Chapter 4 also explores the impact of externality among consumers on brand-influencer collaboration.

1.3. Positioning the Chapters in the Literature

In summary, the presence of various externalities pertaining to marketing strategies highlights their importance in strategic marketing decision-making. This framework provides an overview of externalities related to marketing strategies from three key perspectives: marketplaces, firms, and consumers. Within this framework, each subsequent chapter focuses on examining one or two types of externalities from these different perspectives, as shown in Table 1.1. Chapter 2 introduces *cross-platform network externalities*, which arise between two marketplaces, and discusses their impact on platform pricing strategies. Chapter 3 examines externalities from the firm's perspective (i.e., influencers) in livestream shopping, focusing on two types of externalities: *scheduling consistency*, which refers to the effects of the timing of the previous show on future show scheduling within an agent's activities, and *spillover effects from other influencers,* externalities among peers which capture the externalities exerted from influencers simultaneously streaming as the focal influencer. Chapter 4 delves into externalities from both firms' and consumers' perspectives, particularly exploring the externalities between brands and influencers, as well as those among influencers' audiences, with a focus on their implications for brand-influencer collaboration in influencer marketing.

Table 1.1 Overview of Externalities in Marketing and Chapter Positioning

Research	**Externalities/Spillover Effects**
From Marketplaces' Perspective	
Within a marketplace	
Armstrong (2006)	Cross-side network externalities
Farrell and Saloner (1985)	Network externalities
Katz and Shapiro (1985, 1994)	Network externalities
Rochet and Tirole (2003)	Network externalities
Between two marketplaces	
This thesis (Chapter 2)	**Cross-platform network externalities**
From Firms' Perspective	
Within a firm's activities	
Aaker and Keller (1990)	Reciprocal spillover effects
Balachander and Ghose (2003)	Reciprocal and forward spillover effects
Erdem and Sun (2002)	Externalities between categories
Hennig-Thurau et al. (2009)	Reciprocal spillover effects
Ishihara et al. (2022)	Externalities between child brand and parent brand
John et al. (1998)	Externalities within the umbrella brand
Kireyev et al. (2015)	Externalities between display ads and search ads
Kriejestorac et al. (2020)	Externalities across different social media platforms
Rutz and Bucklin (2011)	Externalities between generic keywords and subsequent branded keywords bidding
Unnava and Aravindakshan (2021)	Spillover effects across different social media platforms
This thesis (Chapter 3)	**Scheduling consistency**
Among peers	
Anderson and Simester (2013)	Advertising externalities
Kashmiri et al. (2016)	Externalities from one firm's data breach to other firms
Liang et al. (2019)	Spillover effects of editor recommendation on platform
Roehm et al. (2006)	Externalities from one firm's scandal to other firms
Ozturk et al. (2019)	Externalities among retailers

Shapiro (2018)	Spillover effects from the advertisement of prescription antidepressants to competitors
Tuchman (2019)	Spillover effects of e-cigarette advertising
Wilbur et al. (2013)	Externalities among TV advertisers
This thesis (Chapter 3)	**Spillover effects from other influencers**
Among business partners	
Amaldoss et al. (2000)	Externalities among business partners
Chennamaneni and Desiraju (2011)	Externalities between business alliances
Geng et al. (2024)	Spillover effects from vertical partnerships
Simonin and Ruth (1998)	Spillover effects of brand alliances
Veugelers (1998)	Externalities among business partners
This thesis (Chapter 4)	**Externalities between brands and influencers**
From Consumers' Perspective	
Armstrong (2015)	Search externalities and "ripped-off" externalities
Chae et al. (2017)	Externalities in the seeding campaign
Goh et al. (2015)	Marketing avoidance externalities
Hann et al. (2008)	Consumer avoidance
This thesis (Chapter 4)	**Word-of-mouth effects among consumers**

2. Cross-platform Network Effects and Platform Pricing

2.1. Introduction

Platform businesses are facilitating services in various aspects of our daily lives, from entertainment (e.g., Netflix, YouTube, TV channels), online shopping (e.g., Amazon, Shopify), and food delivery (e.g., Uber Eats, DoorDash), to vacation and trips (e.g., Expedia, Uber, Airbnb), medical services (e.g., Sharecare, Maple), and business operations (e.g., Zoom, MS Teams). It is increasingly common for consumers to interact with multiple platforms. Some even make bundled choices, either intentionally or through contractual obligations. For instance, a notable number of Uber drivers are registered with both UberX and Uber Eats. Similarly, individuals who purchase a Kobo e-reader often begin buying from the Barnes & Noble Book Store. Many households opt for streaming packages that include both Netflix and ESPN+. In the realm of two-sided platforms, users who engage with multiple platforms are termed *multi-homing users* or *multi-homers*. When two platforms have a substantial overlap of multi-homing users, they become interconnected and exert influence on one another. This interconnection leads to the emergence of *cross-platform network effects*, which in turn affect the pricing and management strategies of the platforms involved.

Cross-platform network effects influence interconnected platforms via multi-homing users, with the first layer of influence emanating from the sheer number of such users. Multi-homing users interact with users on the opposite side of two platforms simultaneously. Therefore, the number of multi-homing users affects and is affected by the other-side users via cross-side network externalities of both platforms simultaneously. Consequently, changes on one platform will lead to changes on the other platform through the number of multi-homing users. For example, as many drivers register for both UberX and Uber Eats, high demand for drivers from passengers on UberX attracts a substantial pool of multi-homing drivers. This, in turn, prompts more restaurants to use Uber Eats, thereby setting off a ripple effect across the platforms.

The second layer of cross-platform network effects emerges from the utilities that multi-homing users derive, shaped by the synergies they encounter while using both platforms. When the synergies are positive, multi-homing users reap additional benefits. The growth of one platform encourages multi-homing users to engage more with the other platform, thereby uplifting both. For instance, multi-homing across an e-commerce platform like Amazon and a payment platform like PayPal can enhance the overall shopping experience. Amazon's rapid expansion has been in sync with PayPal's growth. On the flip side, there can be situations where multi-homing users experience negative synergies, resulting in diminishing marginal utility when engaging both platforms. A boom of one platform could potentially pose a threat to the other platform. As an example, many restaurants use both DoorDash and Uber Eats for food delivery. Yet, as the services on the two platforms are substitutes, a burst of DoorDash can adversely affect the frequency with which restaurants use Uber Eats.

Two layers of impacts complicate the understanding of cross-platform network effects and their implications for platforms' strategic pricing decisions. Even when platforms are independently operated, they can still be interconnected through multi-homing users and are subject to cross-platform network effects emanating from other platforms. However, how these effects reshape platform businesses and influence their strategic decisions remains largely unexplored territory. Some platforms attempt to leverage the cross-platform network effects by acquisition or expansion. For example, in 2018, Alibaba acquired Ele.me, a food delivery platform in China, with the intent that an increasing number of consumers would use both Taobao for online shopping and Ele.me for takeout orders. In 2016, Uber launched Uber Eats to expand its business from transportation service to food delivery. Since then, Uber has encouraged drivers to multi-home on both platforms. These practices suggest that cross-platform network effects yield business advantages. However, there is a noticeable understanding gap, both conceptual and quantitative, regarding how these cross-platform network effects emerge and propel interconnected platforms.

Furthermore, the appropriate marketing decisions to make—such as which pricing strategies to employ in a landscape affected by cross-platform network effects, whether among independent or newly acquired or expanded platforms—remain unresolved questions. A few existing studies (Armstrong, 2006; Anderson et al., 2018; Belleflamme & Peitz, 2019) have started to probe this field by investigating pricing strategies of competing platforms that have multi-homing users on one side. However, these models are confined to situations involving competitive relationships between platforms and fall short of providing a systematic understanding of the economic dynamics of cross-platform network effects or their influence on platform pricing in more comprehensive contexts.

We develop an analytical model to investigate the formation and impact of cross-platform network effects between two interconnected platforms that share multi-homing users. Specifically, our model considers platforms with single-homing users on both sides and a group of multi-homing users on one side[3]. These multi-homing users experience either positive or negative synergies when using both platforms. Therefore, both the number of multi-homing users and their utilities engage in cross-platform network effects and influence the platforms' pricing decisions. We first elucidate how cross-platform network effects are formed via cross-side network externalities among different user groups across the two platforms and quantify the overall

[3] We focus on the case where only one side of the platform has multi-homing users to demonstrate the feedback loops and the formation of cross-platform network effects. However, if both sides of the platforms have multi-homing users, we might not fully capture the feedback loops and cross-platform network effects.

multiplying outcome. Leveraging these insights, we explore equilibrium pricing strategies for the two interconnected but independently owned platforms. Our analysis further extends to the scenarios where the platforms collaborate or merge, allowing them to identify and apply customized pricing for multi-homing users.

Specifically, we evaluate cross-platform network effects from the perspective of feedback loops within the two platforms. Feedback loops, arising from the cross-side network externalities, refer to interactive impacts between users on the two sides of a platform — a change in the number of users on one side affects the number of users on the other side of the platform, and this change then goes back to the side where the change is initiated (Rysman, 2004; Evans & Noel, 2008). When two platforms are interlinked via multi-homing users, there are various feedback loops between different groups of users, including the loop between single-homing users on the two different sides within one platform and the loop between multi-homing users and single-homing users on the two platforms. These feedback loops are interrelated and collectively form the cross-platform network effects. We quantify the impact of each type of feedback loop and derive the multipliers by the cross-platform network effects.

Building on the quantified cross-platform network effects, we solve the platforms' equilibrium pricing decisions. When two platforms are interlinked through the multi-homing users on one side but cannot distinguish multi-homing users from single-homing users, platforms charge less on the side with multi-homing users, while their prices on the other side can either increase or decrease, contingent on the synergies that the multi-homing users (on the original side) receive from utilizing the two platform. When the two platforms can separate multi-homing users from single-homing users, cross-platform network effects do not factor into the platforms' pricing for single-homing users. In contrast, the platforms offer multi-homing users a discount related to cross-platform multipliers. Moreover, if the two platforms are merged, the cross-platform network effect will apply to the users' sizes on the two platforms, but not explicitly factor in the integrated pricing decisions.

The remainder of this paper is organized as follows. We summarize the relevant literature in Section 2. In Section 3, we set up our benchmark model. In section 4, we illustrate how feedback loops form cross-platform network effects and derive cross-platform multipliers. In section 5, we derive and analyze platform pricing in the presence of cross-platform network effects when two platforms are separately owned and cannot distinguish multi-homing users. Section 6 examines the scenarios when multi-homing users can be differentiated. Specifically, 6.1 shows the optimal platform pricing when two platforms are independently operated, while section 6.2 discusses the case when two platforms are integrated. We conclude our research in Section 7.

2.2. Related Literature

2.2.1. Cross-side Network Externalities and Feedback Loops

Our paper is related to several streams of research on two-sided platforms. First, there exists a substantial body of literature examining cross-side network externalities and cross-side network effects (Armstrong, 2006; Ambrus & Argenziano, 2009; Chu & Manchanda, 2016; Dubé et al., 2010; Evans & Noel, 2008; Rochet & Tirole, 2003, 2006; Rysman, 2004; Parker & Van Alstyne, 2005). Along this line of research, it is widely acknowledged that cross-side network externality refers to the marginal benefit that a user on one side gets from the interactions with users on the other side, while cross-side network effects refer to the number of users on one side affects the number of users on the other side of the platform, and vice versa (Armstrong, 2006; Evans & Noel 2008; Rochet & Tirole, 2003, 2006; Rysman, 2004). We follow these definitions and advance our understanding of cross-platform network effects when multi-homing users interconnect two platforms.

Furthermore, few studies have identified the feedback loop(s) that arise from cross-side network effects (Evans & Noel, 2008; Jullien et al., 2021; Rysman, 2004; Tremblay, 2017). Rysman (2004) explicitly estimates the feedback loop between consumers and advertisers in the markets of Yellow Pages. Filistrucchi and Klein (2013) explore how price changes on the advertiser side affect the consumer side and, subsequently, the demand on the advertiser side, resulting in a feedback loop due to cross-side network effects. In addition to these empirical studies, Tremblay (2017) broadens this research line by presenting a generalized mathematical model to account for the infinite feedback loops within the demand function for users' interactions on platforms. Julien et al. (2019) further shed light on the feedback loop, highlighting that the interaction benefits between the users on two sides of the platform induce the feedback loop. Drawing upon these studies, we use feedback loops as a systematic tool to delineate the formation of cross-platform network effects.

2.2.2. Platform Relationships

A substantial extant literature has examined the influence of platform relationships on various aspects of platform strategies, including pricing (Armstrong, 2006; Armstrong & Wright, 2007; Bakos & Halaburda, 2020; Belleflamme & Peitz, 2019; Choi, 2010; Doganoglu & Wright 2006; Gabszewicz & Wauthy, 2004; Liu et al., 2019), tying (Amelio & Jullien, 2012; Choi, 2010; Choi et al., 2017), entry strategies (Amelio et al., 2020; Correia-da Silva et al., 2019; Jullien, 2011; Tan & Zhou, 2019; Vasconcelos, 2015;), and mergers (Anderson et al., 2019; Baranes et al., 2019; Chandra & Collard-Wexler, 2009; Jeziorski, 2014).

This line of literature mainly focuses on platforms that offer substitutive services and compete directly. Many of the existent analytical models (Armstrong, 2006; Armstrong & Wright, 2007; Bakos & Halaburda, 2020; Belleflamme & Peitz, 2019; Hagiu, 2006, 2009; Hagiu & Halaburda, 2014) employ Hotelling setting to model the competition between two platforms. While the Hotelling framework adeptly captures users' preferences between two platforms, it, in most cases, presumes a saturated market where the aggregate number of prospective users of the two platforms is constrained. In those models, the competition by the two platforms for single-homing users often evolves into a near zero-sum game, and the assumption of multi-homing — either on one side or both sides — shapes the platform competition outcome. In essence, these studies scrutinize platform pricing in contexts where competition is fierce but overlook scenarios in which platforms can experience concurrent growth, even in the face of competition.

Specifically, Armstrong (2006) and Armstrong and Wright (2007) investigate the "competitive bottlenecks" case where users on one side all engage in multi-homing and those on the other side are exclusive to a single platform. Hence, platforms exert monopoly power on the side with multi-homers and compete on the single-homing side. Consequently, the studies, along with many that have followed, suggest that platforms tend to charge excessive prices to multi-homes while subsidizing single-homing users on the other side of the platforms. Unfortunately, these studies largely neglect the surplus effects of multihoming.

Belleflamme and Peitz (2019) introduce partial multi-homing on one side in the two-sided Hotelling framework. Their analysis delves into the allocative effects of multi-homers and shows that the impact of the possibility of multi-homing on the two sides of the two platforms can be either positive or negative. Bakos and Halaburda (2020) further advance this line of inquiry by considering user endogenized multi-homing decisions on both sides. The traditional strategy of subsidizing single-homing users ceases to be optimal when multi-homing is possible on both sides. Their model illustrates strong interdependence between pricing decisions by the two competing platforms but diminishing or even no interdependence between the two sides of the same platform.

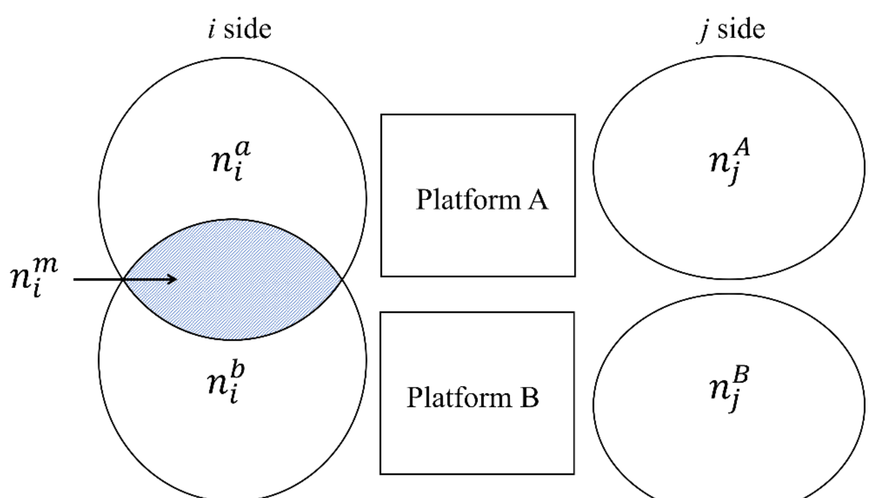
In contrast to existing studies, our research zeroes in on platform dynamics in a more nuanced business landscape where the simultaneous growth of interconnected platforms is feasible. The products or services offered on these platforms may be complementary or not directly related. Even in instances where the offerings are substitutes, a sufficiently expansive pool of potential users exists to permit parallel growth for both platforms. In such contexts, the Hotelling framework falls short. Instead, the success of these platforms is largely driven by cross-sided network externalities among users rather than by constraints of a limited market size. We investigate how multi-homing users serve as crucial connectors between platforms in such environments and how platforms should leverage cross-platform network effects in their pricing.

2.3. Model Setup

When a number of users use two platforms simultaneously, the two platforms are interconnected through these multi-homing users, and cross-platform network effects emerge, affecting both platforms. In this paper, to explicitly demonstrate the role of multi-homing users and the impact of cross-platform network effects, we study a model where two platforms share multi-homing users on one side.

We consider two two-sided platforms, Platform A and Platform B, sharing a group of multi-homing users on one side, denoted as Side *i*. The number of multi-homing users is denoted as n_i^m, and the utility of a representative multi-homing user is u_i^m. Besides multi-homing users, both platforms have a group of single-homing users on Side *i.* The numbers of single-homing users on i-side of the Platforms A and B are n_i^a and n_i^b, and the utilities of representative single-homing users on the i-side of the two platforms are u_i^a and u_i^b, respectively. We denote the total numbers of i-side users of the two platforms as n_i^A and n_i^B, respectively. Hence, $n_i^A = n_i^a + n_i^m$ and $n_i^B = n_i^b + n_i^m$. The two platforms have separated groups of single-homing users but no multi-homing users on the other side, which is denoted as Side j. The number of j-side single-homing users on Platforms A and B are n_j^A and n_j^B, and the utilities of representative j-side single-homing users are u_j^A and u_j^B respectively. We illustrate the model setup in Figure 2.1

Figure 2.1 Model Setup Illustration



Following Armstrong (2006), we assume the number of a group of platform users is an increasing function of the users' utility. Specifically,

On Side i: $n_i^a = \phi_{ia}(u_i^a)$, $n_i^b = \phi_{ib}(u_i^b)$, and $n_i^m = \phi_{im}(u_i^m)$

On Side j: $n_j^A = \phi_{jA}(u_j^A)$, $n_j^B = \phi_{jB}(u_j^B)$

In the later analysis, we simplify the notation, using ϕ_{ia}, ϕ_{im}, ϕ_{ib}, ϕ_{jA} and ϕ_{jB} to represent $\phi_{ia}(u_i^a)$, $\phi_{im}(u_i^m)$, $\phi_{ib}(u_i^b)$, $\phi_{jA}(u_j^A)$ and $\phi_{jB}(u_j^B)$ respectively.

The users' utilities are determined by cross-side network externalities and the prices charged by the platform. Specifically, single-homing users on Side i of platform A pay p_i^A to join the platform and benefit from interactions with j-side users on platform A. Their utility function is $u_i^a = \alpha_i^A n_j^A - p_i^A$, where α_i^A denotes the cross-side network externality generated from each j-side user on i-side users on platform A. In the same vein, i-side single-homing users on platform B pay p_i^B to join the platform and benefit from interactions with all the j-side single-homing users on platform B. Their utility function is $u_i^b = \alpha_i^B n_j^B - p_i^B$, where α_i^B represents the per-unit cross-side network externality from j-side users to i-side users on platform B.

The i-side multi-homing users use both platforms and pay two prices, $p_i^A \; and \; p_i^B$. They gain benefits from interactions with j-side users on both platforms, $\alpha_i^A n_j^A$ and $\alpha_i^B n_j^B$, respectively. In addition, multi-homing users may experience synergies (either positive or negative) when using the two platforms together, which generates an add-on value on their utilities. We model the add-on value as $\delta \cdot \alpha_i^A n_j^A \cdot \alpha_i^B n_j^B$, where the sign of δ depends on whether the synergies are overall positive or negative. If multi-homing users experience positive synergies, such as receiving an extra surplus or saving common costs, $\delta > 0$. For example, Amazon and Twitch facilitate complementary services. Users who use both platforms together gain synergies from enjoying the perks included in the Amazon Prime membership program. The synergies could be negative if multi-homing users incur extra costs or face a constrained capacity when using the two platforms. For instance, though some drivers sign up for both Uber and Lyft, they can only serve one order at a time on one platform; δ is less than zero in such cases. Therefore, the utility function of i-side multi-homing users is:

$$u_i^m = \alpha_i^A n_j^A + \alpha_i^B n_j^B + \delta \alpha_i^A \alpha_i^B n_j^A n_j^B - p_i^A - p_i^B \qquad (1)$$

Noting that a multi-homing user gains a total benefit $\alpha_i^A n_j^A + \delta \alpha_i^A \alpha_i^B n_j^A n_j^B = \alpha_i^A n_j^A \left(1 + \delta \alpha_i^B n_j^B\right)$ from using Platform A, which should be positive according to individual rationality. Otherwise, multi-homing users would not use Platform A. Since $\alpha_i^A n_j^A > 0,\ 1 + \delta \alpha_i^B n_j^B \geq 0$.

Similarly, multi-homing users should get a positive benefit from using Platform B, $\alpha_i^B n_j^B + \delta\alpha_i^A\alpha_i^B n_j^A n_j^B = \alpha_i^B n_j^B(1 + \delta\alpha_i^A n_j^A)$. The individual rationality condition implies $1 + \alpha_i^A n_j^A \geq 0$. We impose these assumptions in Condition 1.

Condition 1: $1 + \delta\alpha_i^A n_j^A \geq 0$ and $1 + \delta\alpha_i^B n_j^B \geq 0$

On Side-*j*, single-homing users on each platform gain benefit from interactions with both *i*-side single-homing users and *i*-side multi-homing users. The per-unit cross-side network externality is denoted as α_j^A and α_j^B respectively. The total benefits are $\alpha_j^A(n_i^a + n_i^m)$. Hence, the utilities of *j*-side single-homing users are:

$$u_j^A = \alpha_j^A(n_i^a + n_i^m) - p_j^A \qquad\qquad u_j^B = \alpha_j^B(n_i^b + n_i^m) - p_j^B$$

Following Armstrong (2006), we assume that two platforms incur per-user costs when facilitating transactions between the uses on their two sides, specifically f_i^A, f_j^A for Platform A and f_i^B, f_j^B for Platform B. Their profits are defined as $\pi^A = n_i^A(p_i^A - f_i^A) + n_j^A(p_j^A - f_j^A)$ and $\pi^B = n_i^B(p_i^B - f_i^B) + n_j^B(p_j^B - f_j^B)$. The two platforms set their prices to maximize their profits.

2.4. Feedback Loops and Cross-Platform Network Effects

Due to cross-side network externalities, *i*-side multi-homing users affect the sizes and utilities of *j*-side users on both Platforms A and B. Meanwhile, multi-homing users' size and utilities are also affected by the latter. Therefore, any changes on Platform A that vary the number of multi-homing users will lead to a change on Platform B, and vice versa. Cross-platform network effects hence emerge. To explore the cross-platform network effects and to better interpret the model analysis results in the later sections, we elaborate on the processes of how an external change impacts the users on different sides of the two platforms, which are commonly named *feedback loops* in the literature.

Existing studies (Rysman 2004, Evans and Noel 2008) have explored how cross-side network externalities form a *feedback loop* — a shift in the number of users on one side influences the benefits of users on the other side and subsequently alters their numbers; as a consequence, the change of the number of the-other-side users impact the benefits of the users on the original side and cause an additional shift of the number of the original-side users. In this way, an initial change on one side of the platform will generate a marginal impact on the **same** side through a feedback loop. In the context of two platforms, various feedback loops exist between different groups of users on the two sides, defining different marginal impacts. We specify these feedback loops and the generated marginal impacts as follows.

Definition 1:

a) There are feedback loops between i-side single-homing users and j-side single-homing users on platform A. The marginal impact through such a feedback loop is:

$$T^{aA} = \frac{\partial u_i^a}{\partial n_j^A} \cdot \frac{\partial n_i^a}{\partial u_i^a} \cdot \frac{\partial u_j^A}{\partial n_i^a} \cdot \frac{\partial n_j^A}{\partial u_j^A} = \alpha_i^A \alpha_j^A \phi'_{ia} \phi'_{jA}$$

b) There are feedback loops between i-side single-homing users and j-side single-homing users on platform B. The marginal impact through such a feedback loop is:

$$T^{bB} = \frac{\partial u_i^b}{\partial n_j^B} \cdot \frac{\partial n_i^b}{\partial u_i^b} \cdot \frac{\partial u_j^B}{\partial n_i^b} \cdot \frac{\partial n_j^B}{\partial u_j^B} = \alpha_i^B \alpha_j^B \phi'_{ib} \phi'_{jB}$$

c) There are feedback loops between i-side multi-homing users and j-side single-homing users on platform A. The marginal impact through such a feedback loop is:

$$T^{mA} = \frac{\partial u_i^m}{\partial n_j^A} \cdot \frac{\partial n_i^m}{\partial u_i^m} \cdot \frac{\partial u_j^A}{\partial n_i^m} \cdot \frac{\partial n_j^A}{\partial u_j^A} = \left(1 + \delta \alpha_i^B n_j^B\right) \alpha_i^A \alpha_j^A \phi'_{im} \phi'_{jA}$$

d) There are feedback loops between i-side multi-homing users and j-side single-homing users on platform B. The marginal impact through such a feedback loop is:

$$T^{mB} = \frac{\partial u_i^m}{\partial n_j^B} \cdot \frac{\partial n_i^m}{\partial u_i^m} \cdot \frac{\partial u_j^B}{\partial n_i^m} \cdot \frac{\partial n_j^B}{\partial u_j^B} = \left(1 + \delta \alpha_i^A n_j^A\right) \alpha_i^B \alpha_j^B \phi'_{im} \phi'_{jB}$$

We use T^{aA} as an example. One unit change in the number of *j*-side users alters the utilities of *i*-side single-homing users on Platform A by $\frac{\partial u_i^a}{\partial n_j^A} = \alpha_i^A$; the marginal change in the number of *i*-side single-homing users on Platform A due to their utility change $\frac{\partial n_i^a}{\partial u_i^a} = \phi'_{ia}$; the change in the number of *i*-side single-homing users consequently affects *j*-side users on Platform A by $\frac{\partial u_j^A}{\partial n_i^a} = \alpha_j^A$; and $\frac{\partial n_j^A}{\partial u_j^A} = \phi'_{jA}$ is the marginal change in the number of *j*-side users on Platform A due to their utility change. Therefore, after a feedback loop, one unit change in the number of *j*-side users on Platform A will cause an additional change in the number of the same group of users by $T^{aA} = \alpha_i^A \alpha_j^A \phi'_{ia} \phi'_{jA}$. T^{bB}, T^{mA} and T^{mB} can be derived in the same way.

Lemma 1: *The marginal impact through the feedback loops between the users on the two sides of Platform A is $T^{aA} + T^{mA}$; and the marginal impact through the feedback loops between the users on the two sides of Platform B is $T^{bB} + T^{mB}$.*

Intuitively, the *i*-side user of each platform contains single-home users and multi-home users. Hence, the marginal change of the number of its *i*-side users by the variation of the number of its *j*-side users is the sum of the marginal change of the number of its *i*-side single-home users and that of the number of multi-home users. Then, the marginal impact of the feedback loops of all users on the two sides of a platform is the sum of the marginal impacts through the feedback loops via its *i*-side single-home users and multi-home users.

It is worth noticing that these feedback loops operate continuously. The marginal impact generated by a feedback loop will trigger the second-round feedback loop and generate an additional marginal impact, which in turn initiates a third round, and so on. It is a recursive and, theoretically, infinite process. If the marginal impacts through the feedback loops are greater than one, i.e., $T^{aA} + T^{mA} \geq 1$ or $T^{bB} + T^{mB} \geq 1$, an initial change can become amplified to an enormous degree through successive feedback loops. This phenomenon is particularly evident in platforms that are in a rapid growth stage, such as Uber and Airbnb. Due to strong cross-side network externalities between sellers and buyers, the marginal impacts through feedback loops can be significantly high. Subsidies are often used as the initial trigger for these feedback loops to spur user growth. These initially subsidized users can then generate a snowball effect, contributing to rapid platform growth.

In contrast to rapidly growing platforms, it's more common for mature platforms to experience marginal impacts through feedback loops that are less than one. Despite the diminishing returns, the recursive feedback loops still amplify changes on either side of the platform, albeit to a finite extent. To ensure long-term sustainability and success, these platforms optimize their pricing strategies to leverage the multiplying effects generated by the feedback loops. This study aims to delve into these typical but intricate scenarios. Condition 2 outlines the necessary condition on marginal impacts through feedback loops to maintain a sustainable business model for platforms.

Condition 2: $0 < T^{aA} + T^{mA} < 1$; $0 < T^{bB} + T^{mB} < 1$;

While Condition 2 holds, we have Lemma 2 as follows.

Lemma 2: *The aggregate impact through the recursive feedback loops within Platform A is* $\sum_{k=0}^{\infty}(T^{aA}+T^{mA})^k = \frac{1}{1-T^{aA}-T^{mA}}$, *the aggregate impact within Platform B is* $\sum_{k=0}^{\infty}(T^{bB}+T^{mB})^k = \frac{1}{1-T^{bB}-T^{mB}}$.

While a change in single-homing users of a platform will be amplified through the recursive feedback loops within that platform, a change in the multi-homing users will be magnified through feedback loops across both platforms. Especially if a variation in one platform alters the number of *i*-side multi-homing users, the initial impact on n_i^m will be transferred to single-homing users of the other platform through feedback loops there. The derivative impacts will then be multiplied within the other platform, as explored in Lemma 2. Cross-platform network effects are hence formed. Furthermore, the impacts in the other platform will circle back to the multi-homing users in an amplified magnitude and will be further amplified through the feedback loops within the initial platform. To facilitate the later analysis, we define *cross-platform multipliers* to depict the multiplying effects on the multi-homing users through the cross-platform network effects.

Definition 2:

a) ***Cross-Platform Multiplier through Platform A,*** $\boldsymbol{\mathcal{M}_A}$, *measures the multiplying effect on the multi-homing users when a change on the multi-homing users is initialized from Platform B and amplified by the feedback loops on Platform A.*

b) ***Cross-Platform Multiplier through Platform B,*** $\boldsymbol{\mathcal{M}_B}$, *measures the multiplying effect on the multi-homing users when a change on the multi-homing users is initialized from Platform A and amplified by the feedback loops on Platform B.*

c) ***Overall Cross-Platform Multiplier,*** $\boldsymbol{\mathcal{M}}$, *measures the overall multiplying effect on the multi-homing users through feedback loops on both platforms.* $\mathcal{M} = \mathcal{M}_A \cdot \mathcal{M}_B$.

Proposition 1: $\mathcal{M}_A = \frac{1-T^{aA}}{1-T^{aA}-T^{mA}}$, *and* $\mathcal{M}_B = \frac{1-T^{bB}}{1-T^{bB}-T^{mB}}$. $\mathcal{M}_A$ *and* $\mathcal{M}_B$ *have the following features:*

i) *Both* $\mathcal{M}_A$ *and* $\mathcal{M}_B$ *are greater than 1, or, cross-platform network effects are always amplifying;*

ii) $\frac{\partial \mathcal{M}_A}{\partial \delta} > 0$ *and* $\frac{\partial \mathcal{M}_B}{\partial \delta} > 0$*, or, cross-platform multipliers are bigger when multi-homing users gain positive synergies from using the two platforms than when they face negative synergies;*

iii) $\frac{\partial \mathcal{M}_A}{\partial T^{aA}} > 0$ *and* $\frac{\partial \mathcal{M}_B}{\partial T^{bB}} > 0$*, or, the cross-platform multiplier through a platform is positively correlated to the marginal impact of the feedback loop within the platform.*

Definition 2 and Proposition 1 offer a quantitative framework for understanding cross-platform network effects. In an economy with interconnected platforms, platforms' marketing strategies —be it in pricing, promotions, or other aspects— should account for two types of amplifying factors. The first is the cross-side network externality native to their own platform, and the second is the cross-platform network effects arising from interconnected platforms. The magnitude of these cross-platform network effects varies, depending on the synergies generated from using multiple platforms simultaneously. For example, the cross-platform network effects are stronger when platforms offer complementary services and weaker when platforms are in competition. Moreover, the strength of the cross-platform network effects correlates positively with the marginal impacts produced by the platform's internal feedback loops. It implies that platforms with pronounced cross-side network externalities don't just benefit in isolation, but also contribute to a more potent multiplying effect across all interconnected platforms.

2.5. Platform Pricing with Cross-platform Network Effects

We now study the platforms' pricing strategy with cross-platform network effects. Even when two platforms are independent and make pricing decisions separately, their pricing decisions are interrelated through cross-platform network effects. Specifically, when a platform changes its prices, it will influence the number of multi-homing users. The change will then be amplified through the feedback loops in the other platform and come back to impact all the users in the original platform. Hence, a platform's pricing decision should consider not only the cross-side network externality within the platform but also the cross-platform network effects between the two platforms.

Platforms A and B are independently owned, and each platform sets its prices on Sides *i* and *j* to maximize its profit. Their profit-maximization objective functions are:

$$\max_{p_i^A, p_j^A} \pi^A = n_i^A\left(p_i^A - f_i^A\right) + n_j^A\left(p_j^A - f_j^A\right) = (n_i^a + n_i^m)\left(p_i^A - f_i^A\right) + n_j^A\left(p_j^A - f_j^A\right),$$

and

$$\max_{p_i^B, p_j^B} \pi^B = n_i^B(p_i^B - f_i^B) + n_j^B\left(p_j^B - f_j^B\right) = \left(n_i^b + n_i^m\right)(p_i^B - f_i^B) + n_j^B\left(p_j^B - f_j^B\right)$$

We next demonstrate the solutions for the equilibrium prices. First, we outline the method used to derive the equilibrium prices, followed by presenting the results with our key findings.

2.5.1. Equilibrium Derivation

Our research builds on Armstrong's (2006) seminar paper on platform pricing. However, his approach may not clearly depict the feedback loops, particularly when the pricing decisions of two platforms are interrelated in the presence of cross-platform network effects. To address this limitation, we propose an alternative method and illustrate the process of deriving equilibrium prices.

As shown in the profit-maximization objective functions, each platform maximizes its own profit by setting the price for users on Sides i and j simultaneously. We obtain the following equations by deriving the first-order conditions with respect to $p_i^A$and p_j^A for Platform A.

$$\left(\frac{\partial n_i^a}{\partial p_i^A}+\frac{\partial n_i^m}{\partial p_i^A}\right)\left(p_i^A-f_i^A\right)+n_i^a+n_i^m+\frac{\partial n_j^A}{\partial p_i^A}\left(p_j^A-f_j^A\right)=0$$

$$\frac{\partial n_i^a}{\partial p_j^A}\left(p_i^A-f_i^A\right)+\frac{\partial n_i^m}{\partial p_j^A}\left(p_i^A-f_i^A\right)+n_j^A+\frac{\partial n_j^A}{\partial p_j^A}\left(p_j^A-f_j^A\right)=0$$

Similarly, we can obtain the equations for platform B:

$$\left(\frac{\partial n_i^b}{\partial p_i^B}+\frac{\partial n_i^m}{\partial p_i^B}\right)\left(p_i^B-f_i^B\right)+n_i^b+n_i^m+\frac{\partial n_j^B}{\partial p_i^B}\left(p_j^B-f_j^B\right)=0$$

$$\frac{\partial n_i^b}{\partial p_j^B}\left(p_i^B-f_i^B\right)+\frac{\partial n_i^m}{\partial p_j^B}\left(p_i^B-f_i^B\right)+n_j^B+\frac{\partial n_j^B}{\partial p_j^B}\left(p_j^B-f_j^B\right)=0$$

By solving the two equations for Platform A and Platform B respectively, we derive the equilibrium prices p_i^A, p_j^A, p_i^B, and p_j^B in terms of partial derivatives:

$$p_i^A=\frac{1}{\left(\frac{\partial n_i^a}{\partial p_i^A}+\frac{\partial n_i^m}{\partial p_i^A}\right)-\left(\frac{\partial n_i^a}{\partial p_j^A}+\frac{\partial n_i^m}{\partial p_j^A}\right)\cdot\left(\frac{\frac{\partial n_j^A}{\partial p_i^A}}{\frac{\partial n_j^A}{\partial p_j^A}}\right)}\cdot\left(-n_i^a-n_i^m+n_j^A\cdot\left(\frac{\frac{\partial n_j^A}{\partial p_i^A}}{\frac{\partial n_j^A}{\partial p_j^A}}\right)\right)+f_i^A$$

$$p_j^A=\frac{1}{\frac{\left(\frac{\partial n_i^a}{\partial p_i^A}+\frac{\partial n_i^m}{\partial p_i^A}\right)}{\left(\frac{\partial n_i^a}{\partial p_j^A}+\frac{\partial n_i^m}{\partial p_j^A}\right)}\cdot\frac{\partial n_j^A}{\partial p_j^A}-\frac{\partial n_j^A}{\partial p_i^A}}\left(\left(n_i^a+n_i^m\right)-\frac{\left(\frac{\partial n_i^A}{\partial p_i^A}+\frac{\partial n_i^m}{\partial p_i^A}\right)}{\left(\frac{\partial n_i^A}{\partial p_j^A}+\frac{\partial n_i^m}{\partial p_j^A}\right)}\cdot n_j^A\right)+f_j^A$$

$$p_i^B = \frac{1}{\left(\frac{\partial n_i^b}{\partial p_i^B} + \frac{\partial n_i^m}{\partial p_i^B}\right) - \left(\frac{\partial n_i^b}{\partial p_j^B} + \frac{\partial n_i^m}{\partial p_j^B}\right) \cdot \left(\frac{\frac{\partial n_j^B}{\partial p_i^B}}{\frac{\partial n_j^B}{\partial p_j^B}}\right)} \cdot \left(-n_i^b - n_i^m + n_j^B \cdot \left(\frac{\frac{\partial n_j^B}{\partial p_i^B}}{\frac{\partial n_j^B}{\partial p_j^B}}\right)\right) + f_i^B$$

$$p_j^B = \frac{1}{\frac{\left(\frac{\partial n_i^b}{\partial p_i^B} + \frac{\partial n_i^m}{\partial p_i^B}\right)}{\left(\frac{\partial n_i^b}{\partial p_j^B} + \frac{\partial n_i^m}{\partial p_j^B}\right)} \cdot \frac{\partial n_j^B}{\partial p_j^B} - \frac{\partial n_j^B}{\partial p_i^B}} \left((n_i^b + n_i^m) - \frac{\left(\frac{\partial n_i^B}{\partial p_i^B} + \frac{\partial n_i^m}{\partial p_i^B}\right)}{\left(\frac{\partial n_i^B}{\partial p_j^B} + \frac{\partial n_i^m}{\partial p_j^B}\right)} \cdot n_j^B \right) + f_j^B$$

Now, we need to calculate the partial derivatives with respect to p_i^A, p_j^A, p_i^B, and p_j^B from the functions that denote the number of users on each side of the two platforms, n_i^a, n_i^b, n_i^m, n_j^A, and n_j^B, respectively. We first illustrate the derivation of optimal price for *i*-side users, p_i^A. Given $n_i^a = \phi_{ia}(u_i^a)$, for single-homing users on platform A, we have $\frac{\partial n_i^a}{\partial p_i^A} = \frac{\partial n_i^a}{\partial u_i^a} \cdot \frac{\partial u_i^a}{\partial p_i^A}$, where $\frac{\partial n_i^a}{\partial u_i^a} = \phi'_{ia}$ is the partial derivative with respect to the utility of single-home users, and $\frac{\partial u_i^a}{\partial p_i^A} = \alpha_i^A \left(\frac{\partial n_j^A}{\partial p_i^A}\right) - 1$ is the partial derivative with respect to p_i^A. Thus, we obtain:

$$\frac{\partial n_i^a}{\partial p_i^A} = \phi'_{ia}\left(\alpha_i^A \left(\frac{\partial n_j^A}{\partial p_i^A}\right) - 1\right)$$

We can similarly derive partial derivatives for *j*-side single-homers $\frac{\partial n_j^A}{\partial p_i^A}$, and *i*-side multi-homers $\frac{\partial n_i^m}{\partial p_i^A}$. As the two platforms are interconnected through multi-homing users, we also derive the partial derivatives with respect to p_i^A on the number of users on each side of the platform B, $\frac{\partial n_i^b}{\partial p_i^A}$ and $\frac{\partial n_j^b}{\partial p_i^A}$ respectively. We list the rest of the equations as follows:

$$\frac{\partial n_j^A}{\partial p_i^A} = \phi'_{jA}\alpha_j^A\left(\frac{\partial n_i^a}{\partial p_i^A} + \frac{\partial n_i^m}{\partial p_i^A}\right)$$

$$\frac{\partial n_i^m}{\partial p_i^A} = \phi'_{im}\left(\delta\alpha_i^A\alpha_i^B n_j^A\left(\frac{\partial n_j^B}{\partial p_i^A}\right) + \delta\alpha_i^A\alpha_i^B n_j^B\left(\frac{\partial n_j^A}{\partial p_i^A}\right) + \alpha_i^B\left(\frac{\partial n_j^B}{\partial p_i^A}\right) + \alpha_i^A\left(\frac{\partial n_j^A}{\partial p_i^A}\right) - 1\right)$$

$$\frac{\partial n_i^b}{\partial p_i^A} = \phi'_{ib}\alpha_i^B\left(\frac{\partial n_j^B}{\partial p_i^A}\right)$$

$$\frac{\partial n_j^B}{\partial p_i^A} = \phi'_{jB}\alpha_j^B\left(\frac{\partial n_i^b}{\partial p_i^A} + \frac{\partial n_i^m}{\partial p_i^A}\right)$$

Using the equations above, we can solve for $\frac{\partial n_i^a}{\partial p_i^A}, \frac{\partial n_j^A}{\partial p_i^A}, \frac{\partial n_i^m}{\partial p_i^A}, \frac{\partial n_i^b}{\partial p_i^A}$ and $\frac{\partial n_j^B}{\partial p_i^A}$. These derivative solutions are then substituted into the first-order condition of the profit maximization function to solve for the optimal price for *i*-side users on Platform A. Similarly, we derive the equilibrium prices, p_j^A, p_i^B, and p_j^B, for *j*-side users on Platform A, *i*-side users on Platform B, and *j*-side users on Platform B respectively.

Finally, by rearranging and simplifying the mathematical formulas of prices regarding the feedback loops and cross-platform multipliers, we derive the optimal pricing decisions for both Platform A and Platform B. We present the results in Lemmas 3 and 4.

2.5.2. Equilibrium Prices

Lemma 3: *The platforms' equilibrium prices on the i-side are*:

$$p_i^A = f_i^A - \alpha_j^A n_j^A + \frac{n_i^a + n_i^m}{\phi'_{ia} + \phi'_{im}\cdot\mathcal{M}_B}$$

$$p_i^B = f_i^B - \alpha_j^B n_j^B + \frac{n_i^b + n_i^m}{\phi'_{ib} + \phi'_{im}\cdot\mathcal{M}_A}$$

Armstrong (2006) examined a single platform's pricing strategy and showed that the platform's equilibrium price on one side, $p_i = f_i - \alpha_j n_j + \frac{n_i}{\phi_i'}$, is composed of three components: i) the cost of providing service, ii) adjusted downward by the external benefit to the other side users, and iii) adjusted upward related to the reciprocal of participation elasticity of the same side users. Lemma 3 shows that when two platforms are interconnected through multi-homing users on one side, their pricing decisions on this side also depend on these three factors. However, the third factor, which is related to the reciprocal of i-side user participation elasticity, has been adjusted due to the existence of multi-homing users and the cross-platform network effects. Using p_i^A as an example, the factor related to i-side user participation elasticity is $\frac{n_i^a + n_i^m}{\phi_{ia}' + \phi_{im}' \mathcal{M}_B}$. Since i-side users consist of single-homing users and multi-homing users, the total number of users on Side i of Platform A is $n_i^a + n_i^m$, and ϕ_{ia}' *and* ϕ_{im}' are in the denominator representing the derivatives of the demand functions of i-side single-homing users and multi-homing users. As explored in Section 4, the changes in multi-homing users will trigger feedback loops in Platform B and will be amplified by the cross-platform network effects. Thus, the derivative of the multi-homing users' demand function is weighted by the *cross-platform multiplier through Platform B,* $\mathcal{M}_B$.

Proposition 2: *When two platforms are interconnected through multi-homing users on one side, they should charge less on that side due to the positive cross-platform network effect, compared to the case where the two platforms are isolated. Moreover, the extent to which a platform should cut its i-side price depends on the cross-platform multiplier through the other platform.*

Proposition 2 can be directly derived from Lemma 3. Intuitively, when two platforms share multi-homing users on one side, the number of multi-homing users can be boosted through the feedback loops on both platforms. Therefore, their participation elasticity, with respect to any platform's price on this side, is amplified by the cross-platform multiplier through the other platform. Compared with the case of two isolated platforms, cutting prices on this side will attract more users. Thus, both platforms are inclined to lower their prices on the side with multi-homing users.

Proposition 3: *When multi-homing users gain positive synergies rather than negative synergies from using the two platforms, the two platforms charge a lower price on Side i*

As shown in Proposition 1, when the i-side multi-homing users experience positive synergies (i.e., δ>0) from using two platforms, cross-platform multiplier through platform B, $\mathcal{M}_B$, is bigger compared with the case when multi-homing users encounter negative synergies (i.e., δ<0). Therefore, the overall participation elasticity of i-side users on both platforms is enhanced when positive synergies are generated from multi-platform use. As a consequence, the two platforms are willing to set lower prices on the side with multi-homing users.

Lemma 4: *The equilibrium j-side prices by Platforms A and B are*:

$$p_j^A = f_j^A - \alpha_i^A n_i^A \cdot \frac{\phi'_{ia}+\phi'_{im}\mathcal{M}_B\cdot\left(1+\delta\alpha_i^B n_j^B\right)}{\phi'_{ia}+\phi'_{im}\mathcal{M}_B} + \frac{n_j^A}{\phi'_{jA}}$$

$$p_j^B = f_j^B - \alpha_i^B n_i^B \cdot \frac{\phi'_{ib}+\phi'_{im}\mathcal{M}_A\cdot\left(1+\delta\alpha_i^A n_j^A\right)}{\phi'_{ib}+\phi'_{im}\mathcal{M}_A} + \frac{n_j^B}{\phi'_{jB}}$$

Lemma 4 shows that the platforms' j-side pricing decisions also depend on three factors, namely, i) the cost of providing service, ii) adjusted downward by the external benefit to the other side users, and iii) adjusted upward by a factor related to the elasticity of the participation of the same side users. As the two platforms share multi-homing users on Side *i,* the second factor, the one related to the external benefit to i-side users, is adjusted due to cross-platform network effects.

We use p_j^A as an example, the factor about external benefit to i-side users is $\alpha_i^A n_i^A \cdot \frac{\phi'_{ia}+\phi'_{im}\mathcal{M}_B\cdot\left(1+\delta\alpha_i^B n_j^B\right)}{\phi'_{ia}+\phi'_{im}\mathcal{M}_B}$. $\alpha_i^A n_i^A$ refers to the initial external benefits to the i-side users from cross-side network externality on Platform A, including both single-homing users and multi-homing users. $\frac{\phi'_{ia}+\phi'_{im}\mathcal{M}_B\cdot\left(1+\delta\alpha_i^B n_j^B\right)}{\phi'_{ia}+\phi'_{im}\mathcal{M}_B}$ is the weighted adjustment on the initial external benefits. As multi-homing users' utility function is $u_i^m = \alpha_i^A n_j^A + \alpha_i^B n_j^B + \delta\alpha_i^A\alpha_i^B n_j^A n_j^B - p_i^A - p_i^B$, one unit change on the external benefit will cause multi-homing users' utility to vary by $1 + \delta\alpha_i^B n_j^B$ units. $\mathcal{M}_B$ $r$epresents the multiplying effect on multi-homing users by cross-platform network effects through Platform B, as elaborated above.

It is worth noting that $\delta > 0$ and $1 + \delta\alpha_i^B n_j^B > 1$ when multi-homing users gain positive synergies from using the two platforms. In such cases, *i*-side multi-homing users on Platform A receive more external benefit from *j*-side users than *i*-side single-homing users do. The extra benefit to multi-homing users' utilities is then magnified by the cross-platform network effect through Platform B. The overall external benefit to *i*-side users of Platform A increases. Hence, Platform A inclines to lower its price to attract more users on Side *j,* which will benefit its *i*-side users, and revenue, more than that in the single-platform case. Meanwhile, if multi-homing users receive negative synergies or face conflicts in using the two platforms, $\delta < 0, 1 + \delta\alpha_i^B n_j^B < 1$. They receive less external benefit from *j*-side users, and the benefit discounts are amplified through the feedback loops in Platform B. The overall external benefit from *j*-side users to *i*-side users on Platform A decreases. Therefore, Platform A' optimal *j*-side price is higher than that in the single-platform case. Platform B' concerns and decisions on *j*-side pricing are the same as those of Platform A. We summarize the result in Proposition 4 as follows.

Proposition 4: *When two platforms are interconnected through multi-homing users on one side, if the multi-homing users receive positive synergies from using the two platforms, the two platforms charge less on the other side, compared with the case that the two platforms are not interconnected; if the multi-homing users experience negative synergies from using the two platforms, the two platforms charge more on the other side, compared with the case that the platforms are not interconnected.*

Essentially, the presence of multi-homing users on one side of the two platforms affects the platforms' pricing decisions on the other side. The other-side users' external benefit on the multi-homing users increases/decreases if multi-homing users experience positive/negative synergies from using the two platforms. It then provides the platforms more/less incentives to attract users with lower prices on the other sides. The magnitude of synergies and the cross-platform network multipliers determine how much the platforms deviate their prices from the optimal level without multi-homing users.

In situations where two platforms offer similar services—such as food delivery rivals DoorDash and Grubhub — many consumers use both platforms. However, service providers like drivers or restaurants often affiliate with just one due to contractual requirements or personal choices. Given the interchangeable nature of these services, consumers utilizing both platforms often find diminishing returns due to redundant features. Proposition 4 suggests that in such competitive landscapes, platforms are likely to levy higher fees on service providers, as they don't anticipate a boost on service providers will lead to a substantial increase in multi-homing consumers, who are hemmed in by competition.

Conversely, when two platforms offer complementary services — like live-streaming service Twitch and e-commerce platform Amazon — the platforms may strategically lower their fees to lure more service providers. The rationale behind this is to cultivate a thriving community of multi-homing consumers who benefit from the symbiotic array of services offered by both platforms. Therefore, the type of services provided, and the corresponding user dynamics play a pivotal role in shaping a platform's pricing strategies for service providers, influenced significantly by cross-platform network effects.

2.6. Model Extension: Platform Pricing with Bundle Price for Multi-homing Users

Multi-homing users connect two platforms and generate cross-platform network effects that benefit both platforms. Typically, multi-homing users pay the same price as single-homing users when accessing individual platforms. However, recognizing the potential of cross-platform network effects, some platforms have begun collaborating to offer “bundled” pricing options to foster the growth of multi-homing users. For example, Amazon Music and Disney+ launched a marketing campaign offering a reduced bundle price to users of both platforms. Similarly, T-Mobile offers a bundle deal where certain plans include Netflix Subscriptions as part of the Package. In this section, we extend our benchmark model to explore how platforms offer a bundle price (denoted as p_i^m) to multi-homing users to leverage cross-platform network effects. We will first examine a scenario where two platforms share the revenue from the multi-homing users, with a bundled price constituted by two independent charges from each platform. We then consider a situation where two platforms merge to optimize pricing for all users on the two platforms.

2.6.1. Bundle Price for Multi-homing Users by Two Independent Platforms

We consider the case where Platforms A and B independently decide how much to charge *i*-side multi-homers for using their own services, p_i^{Am}, and p_i^{Bm} respectively. The total bundled price is the sum of the two independent charges. $p_i^m = p_i^{Am} + p_i^{Bm}$. Then, the utility of i-side multi-homers is:

$$u_i^m = \alpha_i^A n_j^A + \alpha_i^B n_j^B + \delta \alpha_i^A \alpha_i^B n_j^A n_j^B - p_i^m$$

The utilities of single-homing users on the two platforms remain the same. Specifically,

$$u_i^a = \alpha_i^A n_j^A - p_i^A \quad \text{and} \quad u_i^b = \alpha_i^B n_j^B - p_i^B$$

$$u_j^A = \alpha_j^A n_i^A - p_j^A = \alpha_j^A (n_i^a + n_i^m) - p_j^A, \quad u_j^B = \alpha_j^B n_i^B - p_j^B = \alpha_j^B (n_i^b + n_i^m) - p_j^B$$

Platforms A and B optimize their own prices. Their objective functions are:

$$\max_{p_i^A, p_i^{Am}, p_j^A} \pi^A = n_i^a (p_i^A - f_i^A) + n_i^m (p_i^{Am} - f_i^A) + n_j^A (p_j^A - f_j^A) \quad \text{and}$$

$$\max_{p_i^B, p_i^{Bm}, p_j^B} \pi^B = n_i^a (p_i^B - f_i^B) + n_i^m (p_i^{Bm} - f_i^B) + n_j^B (p_j^B - f_j^B)$$

Lemma 5: The equilibrium i-side pricing strategies by Platforms A and B are:

$$p_i^A = f_i^A - \alpha_j^A n_j^A + \frac{n_i^a}{\phi_i^{a\prime}} \quad p_i^{Am} = f_i^A - \alpha_j^A n_j^A + \frac{n_i^m}{\phi_{im}^{\prime} \mathcal{M}_B}$$

$$p_i^B = f_i^B - \alpha_j^B n_j^B + \frac{n_i^b}{\phi_{ib}^{\prime}} \quad p_i^{Bm} = f_i^b - \alpha_j^B n_j^B + \frac{n_i^m}{\phi_{im}^{\prime} \mathcal{M}_A}$$

When a platform can distinguish multi-homing users from single-homing users on Side *i*, it should use discriminate pricing on the two groups of users, as they incur different network effects. Single-homing users directly engage in only the cross-side network effect within the platform. Therefore, their pricing structure mirrors that of a single-platform scenario. Specifically, the price for *i*-side single-homing users comprises three components: i) the per-user service provision cost; ii) a downward adjustment for the external benefit to *j*-side users, and iii) an upward adjustment considering the group (the *i*-side single-homing users) of users' participation elasticity. Despite the cross-platform network effects will affect the equilibrium number of j-side users and consequently impact i-side single-homing users, these effects do not influence the pricing formula for single-homing users.

In setting prices for multi-homing users, the platform also factors in the per-user service cost and a downward adjustment for the external benefits to j-side users within the platform. However, the multi-homing users' participation elasticity with respect to the platform's price will be enlarged by the cross-platform multiplier through the other platform, since the price's impact on the multi-homing users will be boosted via the feedback loops in the other platform. Consequently, the upward adjustment related to the reciprocal of participation elasticity will decrease by a factor corresponding to the cross-platform multiplier through the alternate platform. Furthermore, when multi-homing users receive positive synergies from using the two platforms, the cross-platform multipliers are larger, making multi-homing users more elastic to price changes on either platform. Therefore, both platforms tend to even lower the price for multi-homing users. We encapsulate the two platforms' price discrimination strategies for i-side users in Proposition 5.

Proposition 5: *In the presence of cross-platform network effects, if the platforms can differentiate between single-homing users and multi-homing users, they will apply the same charges to single-homing users as in cases without cross-platform network effects, while providing discounts to multi-homing users. Moreover, if multi-homing users reap positive synergies in using both platforms, the platforms will further decrease their charges for the multi-homing users*.

Lemma 6: *The equilibrium j-side pricing strategies by platforms A and B are*:

$$p_j^A = f_j^A - \alpha_i^A n_i^a - \alpha_i^A n_i^m\left(1 + \delta\alpha_i^B n_j^B\right) + \frac{n_j^A}{\phi'_{jA}}$$

$$p_j^B = f_j^B - \alpha_i^B n_i^b - \alpha_i^B n_i^m \left(1 + \delta \alpha_i^A n_j^A\right) + \frac{n_j^B}{\phi'_{jB}}$$

When platforms can distinguish between single-homing users and multi-homing users on Side *i,* they can also more accurately gauge the external benefit from *j*-side users to the different groups of *i*-side users. Therefore, platforms modify their j-side pricing in accordance with the separate external benefits received by *i*-side single-homing and multi-homing users. The cross-side benefit an *i*-side multi-homing user receives from *j*-side users in one platform is also affected by the synergistic effect of using both platforms. If multi-homing users experience positive synergies, they accrue more benefits from *j*-side users than their single-homing counterparts. Otherwise, they receive less benefit from *j*-side users. As a result, we conclude the platforms' *j*-side pricing strategies in Proposition 6, are analogous to those in Proposition 4.

Proposition 6: *In the presence of cross-platform network effects, if i-side multi-homing users receive positive synergies from using the two platforms, the two platforms reduce their charges on side j, compared with the cases without cross-platform network effects. Conversely, if multi-homing users experience negative synergies from using the two platforms, both platforms impose higher charges on side j.*

2.6.2. Bundle Price for Multi-homing Users by the Integrated Platform

Platforms interconnected via multi-homing users are often incentivized to merge to leverage the cross-platform network effect. Notable examples include Amazon's 2014 acquisition of Twitch to integrate e-commerce and live-streaming, and Expedia's acquisition of HomeAway in 2015 to bolster their travel booking offerings. After the acquisition, integrated platforms can efficiently differentiate multi-homing users and offer them a tailored bundle price. Unlike the pricing strategy of two independent platforms, merged platforms optimize their pricing with the overarching goal of maximizing total integrated profit.

The integrated platforms charge multi-homing users a bundle price p_i^m, and to maximize the total profit as follows.

$$\max_{p_i^a, p_i^b, p_i^m, p_j^A, p_j^B} \pi^{A+B}$$

$$= n_i^a(p_i^A - f_i^A) + n_i^m(p_i^m - f_i^A - f_i^B) + n_i^b(p_i^B - f_i^B) + n_j^A(p_j^A - f_j^A) + n_j^B(p_j^B - f_j^B)$$

Lemma 7: *When the integrated platforms charge a bundle price to the multi-homers, the optimal price for each group of users on Side i* is:

$$p_i^a = f_i^A - \alpha_j^A n_j^A + \frac{n_i^a}{\phi'_{ia}};\ p_i^b = f_i^B - \alpha_j^B n_j^B + \frac{n_i^b}{\phi'_{ib}};\ p_i^m = f_i^A + f_i^B - \alpha_j^A n_j^A - \alpha_j^B n_j^B + \frac{n_i^m}{\phi'_{im}}$$

The optimal price for each group of users on side j is:

$$p_j^A = f_j^A - \alpha_i^A n_i^a - \alpha_i^A n_i^m(1 + \delta\alpha_i^B n_j^B) + \frac{n_j^A}{\phi'_{jA}};\ p_j^B = f_j^B - \alpha_i^B n_i^b - \alpha_i^B n_i^m(1 + \delta\alpha_i^A n_j^A) + \frac{n_j^B}{\phi'_{jB}}$$

Comparing Lemma 7 with Lemmas 5 and 6, the optimal pricing formulas for single-homing users are the same, no matter whether the two platforms are separately owned or integrated. However, it's essential to note that the user numbers will vary after the two platforms merge. Hence, despite identical pricing formulas, the pricing values imposed on single-homing users by the integrated platforms might differ from those set by separate entities.

Interestingly, even considering the pricing formula, the bundle price on multi-homing users levied by the integrated platforms, $p_i^m = f_i^A + f_i^B - \alpha_j^A n_j^A - \alpha_j^B n_j^B + \frac{n_i^m}{\phi'_{im}}$, does not equal to the cumulative prices by the separately owned platforms, i.e., $p_i^m \neq p_i^{Am} + p_i^{Bm} = f_i^A + f_i^B - \alpha_j^A n_j^A - \alpha_j^B n_j^B + \frac{n_i^m}{\phi'_{im}\mathcal{M}_B} + \frac{n_i^m}{\phi'_{im}\mathcal{M}_A}$. Independently owned platforms, in setting their prices, consider the impact of the cross-platform network effect (from the other platform) on the participation elasticity of multi-homing users from their own perspective. However, when the integrated platform sets prices for multi-homing users to maximize the overall profits from both platforms, they only consider multi-homing users' participation elasticity, sidelining cross-platform network effects. Cross-platform network effects still impact multi-homing users, shaping their size, but do not directly factor into the pricing formulas.

Proposition 7: *When the two platforms are merged, the integrated platform internalizes the cross-platform network effects, which are not explicitly listed in the formula.*

Table 2.1 summarizes the equilibrium prices in the three scenarios discussed in subsections 2.5 and 2.6.

Table 2.1 Summary of Equilibrium Prices in Different Scenarios

	i-side prices	*j*-side prices
Separately Owned without a bundle price.	$p_i^A = f_i^A - \alpha_j^A n_j^A + \frac{n_i^a + n_i^m}{\phi'_{ia} + \phi'_{im}\mathcal{M}_B}$ $p_i^B = f_i^B - \alpha_j^B n_j^B + \frac{n_i^b + n_i^m}{\phi'_{ib} + \phi'_{im}\mathcal{M}_A}$	$p_j^A = f_j^A - \alpha_i^A (n_i^a + n_i^m) \cdot \frac{\phi'_{ia} + \phi'_{im}\mathcal{M}_B \cdot (1 + \delta\alpha_i^B n_j^B)}{\phi'_{ia} + \phi'_{im}\mathcal{M}_B} + \frac{n_j^A}{\phi'_{jA}}$ $p_j^B = f_j^B - \alpha_i^B (n_i^b + n_i^m) \cdot \frac{\phi'_{ib} + \phi'_{im}\mathcal{M}_A \cdot (1 + \delta\alpha_i^A n_j^A)}{\phi'_{ib} + \phi'_{im}\mathcal{M}_A} + \frac{n_j^B}{\phi'_{jB}}$
Separately Owned with a bundle price.	For single-homing users on Platform A: $p_i^A = f_i^A - \alpha_j^A n_j^A + \frac{n_i^a}{\phi'_{ia}}$ For multi-homing users on Platform A: $p_i^{Am} = f_i^a - \alpha_j^A n_j^A + \frac{n_i^m}{\phi'_{im}\mathcal{M}_B}$ For single-homing users on Platform B: $p_i^B = f_i^B - \alpha_j^B n_j^B + \frac{n_i^b}{\phi'_{ib}}$ For multi-homing users on Platform B: $p_i^{Bm} = f_i^b - \alpha_j^B n_j^B + \frac{n_i^m}{\phi'_{im}\mathcal{M}_A}$	$p_j^A = f_j^A - \alpha_i^A n_i^a - \alpha_i^A n_i^m (1 + \delta\alpha_i^B n_j^B) + \frac{n_j^A}{\phi'_{jA}}$ $p_j^B = f_j^B - \alpha_i^B n_i^b - \alpha_i^B n_i^m (1 + \delta\alpha_i^A n_j^A) + \frac{n_j^B}{\phi'_{jB}}$
Integrated with a	$p_i^a = f_i^A - \alpha_j^A n_j^A + \frac{n_i^a}{\phi'_{ia}}$	$p_j^A = f_j^A - \alpha_i^A n_i^a - (\alpha_i^A + \delta\alpha_i^A \alpha_i^B n_j^B) n_i^m + \frac{n_j^A}{\phi'_{jA}}$

bundle price.	$p_i^b = f_i^B - \alpha_j^B n_j^B + \frac{n_i^b}{\phi'_{ib}}$ $p_i^m = f_i^A + f_i^B - \alpha_j^A n_j^A - \alpha_j^B n_j^B + \frac{n_i^m}{\phi'_{im}}$	$p_j^B = f_j^B - \alpha_i^B n_i^b - (\alpha_i^B + \delta\alpha_i^B \alpha_i^A n_j^A) n_i^m + \frac{n_j^B}{\phi'_{jB}}$

2.7. Conclusion and Discussion

As platform businesses thrive, interconnection between platforms through multi-homing users becomes increasingly popular. This paper systematically examines the formation of cross-platform network effects between interconnected platforms and their impacts on platform pricing strategies. Specifically, we mainly focus on the case where only users on one side multi-home so that we can clearly elucidate how feedback loops between different groups of users cumulatively form the cross-platform network effects and define *cross-platform multipliers*, which can be used to quantify the multiplying effects from one platform to the other one via multi-homing users.

We then explore how cross-platform network effects reshape the platforms' pricing decisions. Independent platforms aim to reduce prices on the interconnected side — i.e., the side with shared multi-homing users — in order to harness cross-platform network effects for user growth. Meanwhile, platforms may either elevate or diminish prices on the opposite side, contingent upon the positive or negative synergies experienced by multi-homing users. Such price fluctuations are dictated by the relevant cross-platform multipliers.

We extend our study to scenarios where the platforms can distinguish between multi-homing users and single-homing users for differential pricing. Platforms are thereby empowered to harness cross-platform network effects more accurately by targeting exclusive discounts at multi-homing users, which depends on cross-platform multipliers. Additionally, in the scenario of platform consolidation, the cross-platform network effects become embedded in the user bases on both platforms but are not explicitly present in the integrated pricing decisions.

Our research expands the existing literature on pricing decisions in platform relationships. While the majority of existing studies rely on the Hotelling framework where the limited market size and specific setting of multi-homing shape the equilibrium pricing, we shift the focus to cross-platform network effects. These effects emerge from cross-sided network externalities on individual platforms and are augmented through feedback loops via multi-homing users. Our model is versatile and applicable to scenarios where platforms are complementary, unrelated, or competitive, but always within a market environment conducive to growth. We believe our insights will serve as a valuable roadmap for platform businesses looking to refine their pricing strategies in response to interconnections with other platforms. Furthermore, our model employs general functions to define user demand, user value functions, and synergy effects on multi-homing users, making it a robust framework for future investigations on platform business decisions in various specific relationship.

It is worth noting that our research employs a model in which two platforms share multi-homing users exclusively on one side. It allows us to distinctly demonstrate the mechanism of cross-platform network effects from this group of multi-homing users and their impacts on both sides (one with multi-homing users and one without multi-homing users) of the two interconnected platforms. In cases where two platforms share multi-homing users on both sides, cross-platform network effects from two groups of multi-homing users can be accumulated in shaping platforms' pricing decisions and equilibrium outcomes.

3. Strategic Timing in Livestream Shopping

3.1. Introduction

Livestream shopping is a new business model where influencers promote and sell products on behalf of brands, offering consumers an interactive and entertaining online shopping experience through real-time livestream shows. This model has experienced remarkable growth in recent years. In China, the annual sales of livestream shopping surged from USD 58.8 billion in 2019 to over USD 688.8 billion in 2023, accounting for 31.9% of China's E-tailing business (Statista, 2024). The trend is extending its reach to North America. The sales revenue in livestream shopping in the U.S. grew from USD 20 billion in 2020 to USD 50 billion in 2023, with a projected increase of 36% by 2026 (Statista, 2025). Major e-commerce and retail players, including Amazon, Shopify, Walmart, Nordstrom, and TikTok, have ventured into the livestream shopping landscape. Livestream shopping is poised to reshape the future of online retail (The Economist, 2021).

This burgeoning business model revolutionizes online retailing by creating a highly concentrated shopping experience. Compared to conventional e-commerce, which allows consumers to browse product information and complete transactions at any time, livestream shopping condenses product demonstrations, live communication with influencers, and transactional activities into a few hours of a livestream show. During this short timeframe, consumers watch live demonstrations, engage with influencers and other consumers, and make real-time purchase decisions. Influencers, to ensure the success of these intensive shows, often dedicate days to meticulously scripting and preparing for their shows in advance. Consequently, the timing of a livestream show emerges as a critical strategic decision, influencing both audience size and sales performance.

Influencers independently determine when to livestream their shows in the highly dynamic livestream shopping market. Unlike brick-and-mortar stores with steady operating hours or television broadcasts with fixed schedules, influencers do not follow rigid schedules for their livestream shows. The day of the week and the time of day of their livestreams constantly vary based on viewer activity and the presence of other influencers. With hundreds of millions of viewers and influencers active on livestream platforms that operate 24/7, the number of viewers and shows fluctuates over time. This ever-changing market poses a significant challenge for influencers as they strive to determine the optimal timing for their shows.

Accordingly, influencers aim to stream during peak days and high-demand hours to attract larger audiences and boost sales (Krings, 2024). In addition, influencers must anticipate the audience shift due to overlapping shows, particularly those hosted by popular influencers with tens of millions of followers. While popular influencers can draw substantial audiences to the platform and increase overall demand, they may also divert viewers from other concurrent shows, reducing audience sizes for influencers streaming simultaneously. Moreover, influencers face a complex decision about whether to maintain a consistent streaming schedule. This decision involves weighing the trade-off between fostering habitual viewing behaviors among loyal audiences (Pollak & Wales, 1992) and the potential decline in purchase propensity due to audience fatigue from repetitive schedules. Most importantly, much like conventional marketing decisions in which firm size significantly influences strategies and outcomes, influencers' timing decisions and show success are shaped by their popularity.

While academic research on livestream shopping is growing rapidly, the condensed transactional nature of this business model remains underexplored, and influencers' timing strategies have largely been overlooked. Despite influencers regularly adjusting the timing of their livestream shows, little academic guidance exists to help them navigate or optimize their decisions. This study aims to provide a systematic understanding of timing decisions in livestream shopping, examining how key timing factors affect show outcomes and how influencers of varying popularity approach timing decisions.

We develop a theoretical framework that identifies three key timing factors: *time patterns*, including day-of-the-week and time-of-day effects; *spillover effects*, capturing the impact from top influencers and celebrities who stream concurrently with the focal influencer; and *scheduling consistency*, measuring whether an influencer streams consistently on the same days or at the same time intervals. To empirically investigate the impact of these factors on show outcomes, we collected data of 15,711 shows by 398 influencers from a leading livestream shopping platform in China. We first employ a fixed-effect panel regression model to examine how these timing factors affect livestream show outcomes, specifically show viewership and show sales. We then use a logit regression model with fixed effects to investigate whether influencers incorporate these factors in their timing decisions. To distinguish the timing strategies of influencers with different levels of popularity, we categorize them into two groups: ***top influencers***, defined as those with over 10 million followers, and ***established influencers***, defined as those with follower counts between 1 million and 10 million. We analyze each group separately to understand their decision-making processes.

Our regression results reveal several key insights into the roles of time patterns, spillover effects, and schedule consistency in influencers' timing decisions and their impact on show outcomes. First, evening shows attract higher viewership and generate more sales, aligning with both top and established influencers' preference for streaming at this time. Second, while established influencers experience lower viewership and sales on weekdays—particularly

Wednesdays and Thursdays—they still prefer streaming on weekdays over weekends. In contrast, day-of-week effects have little impact on top influencers, though they tend to avoid streaming on Mondays, Fridays, and Saturdays. Third, our findings reveal a positive spillover effect from top influencers and celebrities on established influencers' shows. On average, each additional top influencer or celebrity streaming simultaneously increases an established influencer's viewership by 0.5% and sales by 0.7% on average. However, despite these benefits, established influencers tend to avoid streaming alongside popular influencers, suggesting a disconnect between their timing decisions and actual market dynamics. Finally, we find no significant evidence that scheduling consistency improves show outcomes in terms of viewership or sales. Yet, both top and established influencers exhibit a strong tendency to follow a consistent schedule, indicating that their timing decisions may be influenced by factors beyond immediate performance metrics.

Our study provides new insights into influencers' timing decisions and the role of timing in shaping show outcomes, contributing to research on demand dynamics and influencer marketing strategies. The finding that top influencers and celebrities generate positive spillover effects highlights their unique role in expanding platform-wide viewership, reinforcing the symbiotic relationship between popular influencers and livestream shopping platforms. This challenges the assumption that influencers compete for a fixed audience and instead demonstrates how high-profile influencers drive overall market demand. Second, the discrepancies between influencers' timing choices and actual show outcomes suggest that influencers may overlook the influence of popular influencers while overestimating the benefits of scheduling consistency. These insights encourage influencers to reassess their scheduling strategies and adopt data-driven timing decisions that align with actual market dynamics. Finally, these discrepancies highlight the complexity of timing decisions. Influencers do not optimize solely for immediate viewership and sales; they also consider operational constraints, cost efficiency, and long-term audience loyalty. This contributes to research on strategic timing and helps managers balance short-term performance with sustainable audience growth. By providing these insights, this study lays the foundation for further research on timing strategies in influencer marketing and the trade-offs influencers face in digital marketplaces.

The remainder of this paper is structured as follows. The next section reviews the relevant literature, followed by the development of our theoretical framework and hypotheses. We then provide an overview of the research context and data before introducing the methodology. Next, we analyze the impact of key timing factors on show outcomes and examine how these factors shape influencers' timing decisions. The discussion section explores the discrepancies between influencers' scheduling choices and actual show performance. Finally, we conclude with our theoretical contributions, managerial implications, research limitations, and directions for future research.

3.2. Literature Review

Our research is closely related to the literature on livestream shopping and studies on timing strategies.

3.2.1. Literature on Livestream Shopping

Academic research on livestream shopping has grown significantly over the past two years, reflecting the rise of this innovative e-tailing model. Much of this research has focused on influencer-brand relationships, particularly the strategic selection of influencers to maximize sales outcomes. For instance, Gu et al. (2024) find that while prominent influencers reach wider audiences, smaller influencers often achieve higher conversion rates. Similarly, Li et al. (2024)

suggest that startups benefit from partnering with either highly popular influencers or those with smaller, loyal followings, whereas established firms should prioritize influencers with moderate popularity. Xiao et al. (2024) further highlight that commitments to sales volume are mutually beneficial for merchants and influencers, emphasizing the importance of alignment between influencer scale and merchant goals. In addition to influencer selection, many studies examine selling and promotional strategies during livestream shows. Bharadwaj et al. (2022) and Lin et al. (2021) highlight how influencer emotional expressions enhance sales and viewer engagement, while Huang et al. (2024) propose optimal promotion insertion strategies tailored to audience involvement levels.

Despite this burgeoning literature, limited attention has been given to the condensed transactional nature of livestream shopping and its associated timing concerns. Timing decisions remain a critical yet unexplored dimension of this business model. Our study addresses this gap by providing a systematic framework to analyze the factors impacting influencers' timing decisions and their implications for livestream show outcomes.

3.2.2. Literature on Strategic Timing

Timing decisions are fundamental in various business contexts, including retailing, new product launches, movie releases, TV and radio commercials, and social media posting. Academic studies (summarized in Table 3.1) have identified several key factors that shape practitioners' timing decisions and their impacts on business outcomes.

First**,** time patterns, such as the week of the year, day of the week, or time of day, affect timing decisions and marketing outcomes. For example, sales during peak seasons can exceed several months of off-season sales, making seasonal timing crucial (Radas & Shugan, 1998).

Similarly, to capture the peak demand during the opening weekend, movie distributors strategically release films on Fridays (Einav, 2007). Radio stations schedule commercials during the after-work hours to enhance audience exposure (Sweeting, 2006, 2009), while the timing of the social media posts also influences the performance (Kanuri et al., 2018). In addition, retail demand in both online and offline markets also fluctuates by day of the week and time of day (Bhatnagar et al., 2017; East et al., 1994).

Second, spillover effects from competitors or peers are another critical factor. In the movie industry, simultaneous releases of films can intensify the competition, as films vie for the same audience, while staggering release times can mitigate direct rivalry (Chiou, 2007; Einav, 2002, 2007; Krider & Weinberg, 1998). In advertising, concurrent TV or radio commercials during peak hours can deter channel switching and concentrate audience attention (Epstein, 1998; Sweeting, 2006, 2009; Yao et al., 2017). Moreover, a recent study in live streaming suggests that when entrant streamers shift to a new category, they bring their viewers as additional viewers to the existing streamers who are in the same category, generating a positive spillover effect (Zhao et al., 2023).

Finally, scheduling consistency has been shown to influence business performance. For instance, consistent schedules improve customer retention and engagement (Liu-Thompkins & Tam, 2013; Shah et al., 2021). Furthermore, maintaining regularity in timing builds audience habits, which can have long-term positive effects on business outcomes (East et al., 1994; Kahn & Schmittlein, 1989; Kesavan et al., 2022).

While these studies provide valuable insights into timing decisions in traditional industries, their findings and implications may not be applicable to livestream shopping, given its distinct market dynamics and mechanisms. Our study aims to address this limitation by examining the dynamic and context-specific nature of timing decisions in the livestream shopping market.

Table 3.1 Overview of Selected Literature Related to Strategic Timing

Research	**Context**	**Main Drivers in timing decisions**		
		Time patterns	*Scheduling consistency*	*Spillover effects*
Bayus et al. (1997)	New product launch	No	No	From competitors
Bhatnagar et al. (2017)	Online retail	Day of the week; Time of day	No	No
Chiou (2007)	Movie	Day of the week	No	From similar movies
Danaher & Mawhinney (2001)	Television programs	Day of the week; Time of day	No	No
Danaher et al. (2015)	Mobile coupons	Day of the week; Time of day	No	No
East et al. (1994)	Retail stores	Day of the week; Time of day	No	No
Einav (2002, 2007)	Movie	Day of the week	No	From similar movies
Epstein (1998)	TV network	Day of the week; Time of day	No	From other TV networks
Kanuri et al. (2018)	Social media posting	Day of the week; Time of day	No	No
Kahn & Schmittlein (1989)	Retail stores	Day of the week; Time of day	Day consistency; Time consistency	No
Kesavan et al. (2021)	Retail stores	Day of the week; Time of day	Day consistency; Time consistency	No
Liu-Thompkins & Tam (2013)	Retail stores	Time of day	Time consistency	No
Lu et al. (2022)	Retail stores	Day of the week; Time of day	Day consistency; Time consistency	No
Radas & Shugan (1998)	Movie	Day of the week	No	From similar movies
Shah et al. (2014)	Retail stores	Time of day	Time consistency	No
Sweeting (2009)	Ratio commercial	Time of the day	No	No
Talay et al. (2024)	New product launch	Week of the year	No	From competitors
Yao et al. (2017)	TV commercial	Day of the week	No	From commercials on other channels
Zhang et al. (2023)	Retail stores	Time of the day	No	No
Zhao et al. (2023)	Livestreaming	Time of the day	No	From new entrants
This study	**Livestream shopping**	**Day of the week; Time of day**	**Day consistency; Time consistency**	**From top influencers and celebrities**

3.3. Theoretical Framework and Hypothesis Development

Extant research on timing strategies has highlighted three key factors − time patterns, spillover effects, and scheduling consistency − as critical determinants of business performance in traditional industries. These factors also play a pivotal role in shaping show outcomes in the livestream shopping market. The number of viewers on livestream shopping platforms fluctuates across time slots, directly affecting the viewership of individual shows. Moreover, variations in the number of concurrent shows, especially those streamed by popular influencers, generate contemporary spillover effects on focal shows. Finally, shows adhering to a consistent schedule might attract more followers with enhanced engagement. In this section, we explore the detailed effects of these factors within the context of livestream shopping.

Remarkably, the influence of these factors on livestream shopping shows may vary considerably depending on an influencer's popularity and social influence. Existing research in traditional industries has demonstrated that firm size and marketing power significantly shape marketing strategies (Laforet, 2008; Liu, 1995; Mariuzzo et al., 2003; Sung et al., 2022; Woolley et al., 2023) and performance (Amato & Amato, 2004; Goddard et al., 2006; Hall & Weiss, 1967; Lee, 2009). Similarly, in livestream shopping, an influencer's popularity—as reflected by their follower count—signals their attractiveness and credibility to the viewers. Consequently, the mechanisms through which timing factors affect performance are likely to differ between highly popular influencers and less prominent ones. To comprehensively examine the role of timing factors in the livestream shopping market, this study investigates their impact on influencers with varying levels of popularity. Specifically, we define ***top influencers*** as those with over 10 million followers, while ***established influencers*** are defined as those with follower counts ranging between 1 million and 10 million.

3.3.1. Time Patterns

Time patterns capture the demand shift in the livestream shopping market based on the *day of the week* and *time of day*. Market demand for online shopping fluctuates throughout the week as consumers' activities are influenced by their work schedules. Consumers tend to have more leisure time on weekends (Rybczynski, 1991; Zhong et al., 2008), increasing their likelihood of making online purchases (Bhatnagar et al., 2017). This increased leisure time on weekends allows consumers to join the livestream shows to interact with influencers and purchase products, resulting in higher demand during weekends. Consequently, this day-of-the-week effect is expected to benefit both established and top influencers, resulting in an increase in the viewership and sales for their livestream shows over the weekend.

Additionally, market demand fluctuates throughout the day, as consumers' ability to process information with working memories varies with diurnal patterns (Kanuri et al., 2018). Working memory for most consumers peaks in the morning, declines as the day progresses, and increases in the evening again. This change in working memory likely results in varying levels of social media engagement (Kanuri et al., 2018). Furthermore, consumers exhibit higher self-control over personal desires in the morning, which diminishes as the day progresses (Phang et al., 2019). In the evening, reduced self-control coupled with increased leisure time likely increases consumers' inclination to make purchases during livestream shows. As a result, shows hosted by both established and top influencers are expected to perform better in terms of audience size and sales during the evening. Thus, we posit the following hypotheses:

H1 Show outcomes of established influencers and top influencers are better on weekends.

H2 Show outcomes of established influencers and top influencers are better in the evening.

3.3.2. Spillover Effects

Prior research in marketing and economics has identified both positive and negative spillover effects from competitors or peers. A large number of competitors can attract more consumers, leading to positive spillover effects that boost overall market demand (Einav, 2007; Lu & Yang, 2017; Radas & Shugan, 1998; Zhao et al., 2023). Conversely, a greater number of competitors or the presence of a strong competitor can intensify the competition. Firms strategically avoid direct competition (Einav, 2002), particularly when one firm is weaker than its competitors (Krider & Weinberg, 1998). Thus, the net impact of spillover effects from competitors depends on the relative strength of these two opposing forces.

Applying this concept to the livestream shopping market, where thousands of influencers stream simultaneously on a platform, the spillover effects from top influencers and celebrities are crucial to the concurrent shows. Top influencers or celebrities, due to their prominence, may draw viewers away from concurrent shows streamed by other influencers, thereby decreasing viewership and sales of those shows. However, they may also attract a significant influx of new viewers to the platform, who may explore other shows on the platform. The net impact of the spillover effects depends on the balance between audience losses to top influencers and celebrities and audience gains generated by their presence.

These spillover effects apply to top and established influencers differently. Established influencers, with relatively lower social popularity and influence, are likely to experience an overall negative spillover effect from top influencers. In contrast, top influencers, who have comparable levels of fame and larger follower counts, may experience a more balanced combination of positive and negative spillover effects. As a result, the overall spillover effects from top influencers and celebrities on a focal top influencer’s show are likely to be insignificant. Based on these considerations, we propose the following hypotheses:

H3 The spillover effects from top influencers and celebrities weaken the show outcomes of established influencers.

H4 The spillover effects from other top influencers and celebrities on the show outcomes of the focal top influencers are insignificant.

3.3.3. Scheduling Consistency

Existing research in marketing suggests that consistent actions lead to predictability, which increases trust (Moorman et al., 1993) and enables online users to forecast future exchanges (Hajli et al., 2017). This trust then encourages repeated viewing of the content and enhances the duration of the relationship between online users and social media platforms, increasing the number of viewers and their purchase intentions (Hajli et al., 2017).

In the livestream shopping market, adhering to a consistent schedule enables viewers to regularly allocate time to interact with influencers (Kim & Kim, 2021), fostering a sense of belonging to the influencers' community. This sense of belonging, in turn, increases viewers' likelihood of interacting with influencers and fellow viewers, thereby enhancing overall participation and engagement (Farivar et al., 2022). A consistent streaming schedule also allows viewers to plan their activities around showtimes, encouraging regular attendance and the formation of viewing habits. This habitual participation fosters active engagement between viewers and influencers, as well as among viewers themselves, creating a communal and immersive experience. By maintaining consistent schedules, both established influencers and top influencers may enhance viewers' experiences and improve show outcomes.

Drawing upon the concept of weekly and daily regularities in social media use (Golder et al., 2007), this study examines two dimensions of scheduling consistency[4]: *day consistency*, which refers to influencers streaming their shows on the same day as the previous week; and *time consistency*, pertains to influencers streaming shows during the same time interval as their most recent show. Accordingly, we posit:

H5 Day consistency improves show outcomes of both established influencers and top influencers.

H6 Time consistency improves show outcomes of both established influencers and top influencers.

3.4. Research Context and Data

3.4.1. Data From Douyin

We investigate the livestream shopping market on Douyin in 2021. Launched in 2016, Douyin introduced livestream shopping in 2018. By 2021, it had become one of the largest livestream shopping platforms in China, owning approximately 639.4 million active users (Statista, 2024). That year, over 1 million influencers streamed more than 5.6 million shows (CBNdata, 2022), generating a total gross merchant value of USD 150 billion (WPIC, 2024). Douyin's thriving market makes it an ideal context for examining influencers' timing decisions in livestream shopping.

[4] While *time patterns* capture the fixed effects based on time slots, *schedule consistency* reflects the practice of maintaining a consistent schedule in the same time slots.

We collected data of livestream shopping shows hosted by 500 large influencers on Douyin over a nine-week period from September 6 to November 7, 2021. During this period, each of these influencers maintained a follower count exceeding 1 million. We focused on this group of influencers for two key reasons. First, their large follower counts indicate active and regular live streaming within nine weeks. Second, interviews with industry experts suggest that influencers with over 1 million followers typically exercise autonomy in their strategic decision-making.

To ensure our analysis focuses on influencers' strategic timing decisions, we excluded influencers who do not follow specific timing practices. Specifically, we removed 46 influencers who invited multiple hosts streaming in rotation for extended periods, with show durations ranging from 18 hours to 24 hours. Moreover, 56 celebrities were excluded because their livestream schedules were shaped by other professional commitments, as live streaming was not their priority. As a result, the final dataset consists of 398 influencers who collectively streamed 17,732 shows over nine weeks. Among these shows, 16,307 shows were streamed by 347 established influencers, and 1,425 shows by 51 top influencers. Detailed show attributes include show date, starting time, ending time, duration of the show, varieties of products sold in the show, number of viewers, and sales amount.

3.4.2. Market Context and Preliminary Evidence on Timing in Livestream Shopping

Influencers on Douyin independently determined when to schedule their livestream shows, leading to a diverse array of timing patterns. Some influencers streamed sporadically, while others maintained loosely predictable schedules, though very few adhered to a strictly consistent routine. The number of streaming influencers varied greatly across different sessions, with shifts in availability and activity levels contributing to a constantly changing competitive environment. We provided some model-free analyses to demonstrate the dynamic and complex nature of show timing in the livestream shopping market.

3.4.2.a. Timing patterns

Figure 3.1 presents a heat map depicting the number of influencers streaming by day of the week in our dataset. Among the 398 influencers, the number of streaming influencers fluctuated significantly, ranging from 131 to 235 per day. The ratio between the number of established influencers and top influencers also varied widely every day, ranging from 8.6 to 31.8. This variability suggests that established and top influencers may adopt different approaches to scheduling their livestream shows.

Figure 3.1 The Number of Established/Top Influencers Streaming by Day of the Week

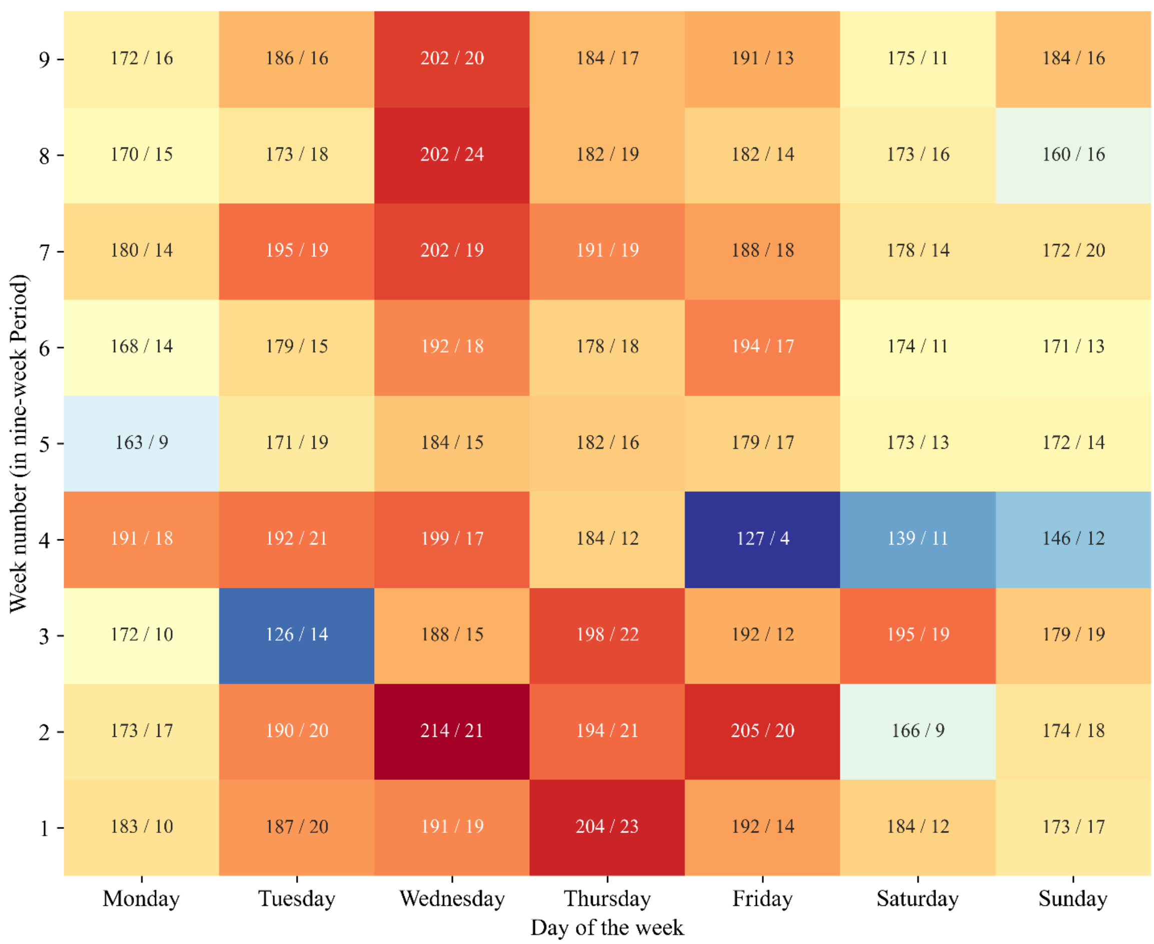


Figure 3.2 and Figure 3.3 illustrate the number of established and top influencers by time of day, respectively. Following prior research (Kanuri et al., 2018; Zhao et al., 2023), we divided each day into four time intervals: *Night* (12:00 A.M. − 5:59 A.M.), *Morning* (6:00 A.M −11:59 A.M), *Afternoon* (12:00 P.M. −5:59 P.M.), and *Evening* (6:00 P.M. −11:59 P.M.). We assigned each show to a time interval in which the majority of its duration occurred. For example, a show that started at 9:30 A.M. and ended at 12:30 P.M. on September 6, 2021. overlapped with the *Morning* interval for 2.5 hours and with the *Afternoon* interval for 0.5 hours; therefore, it was classified under the *Morning* interval on September 6. Overall, both established influencers and top influencers were most active in the *Evening,* followed by the *Afternoon*, with the fewest influencers streaming during the *Night*.

Figure 3.2 The Number of Established Influencers Streaming by Time of Day Over the Nine-Week Period

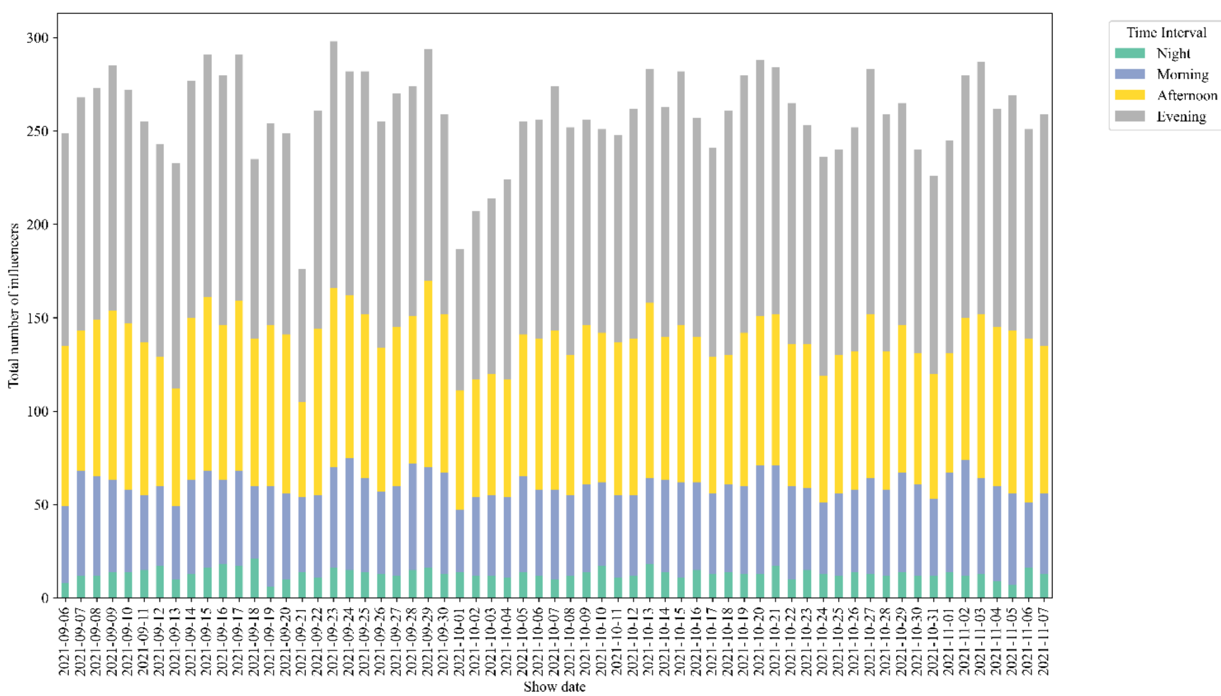
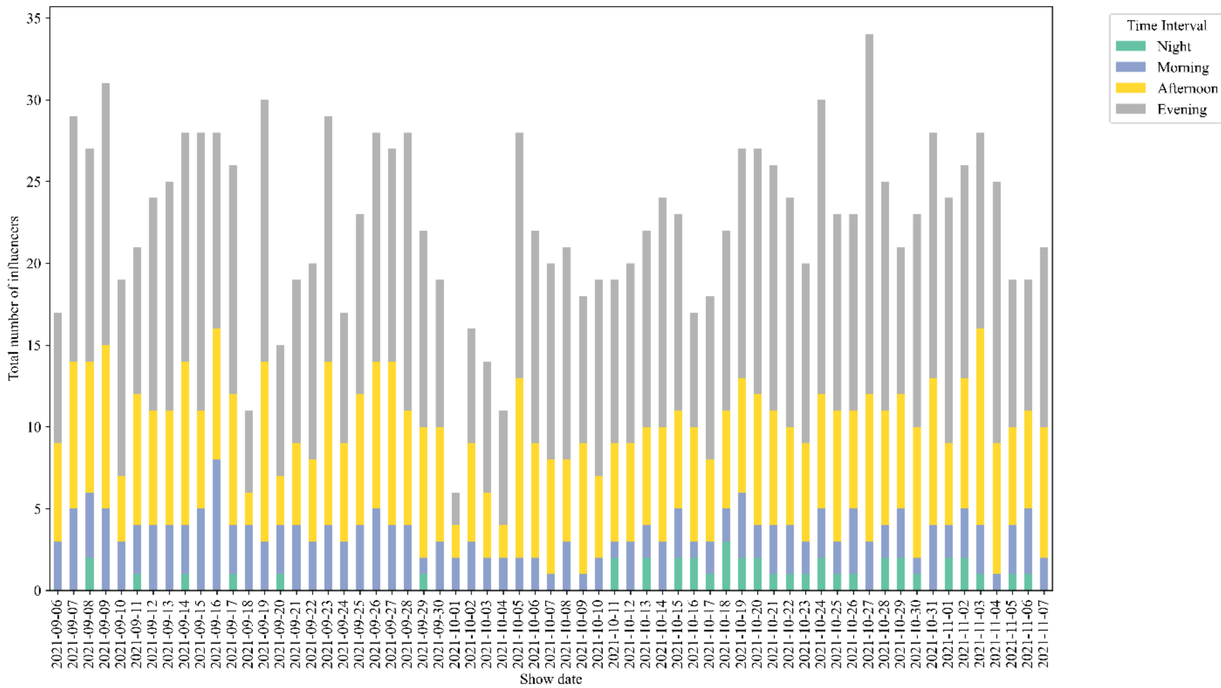


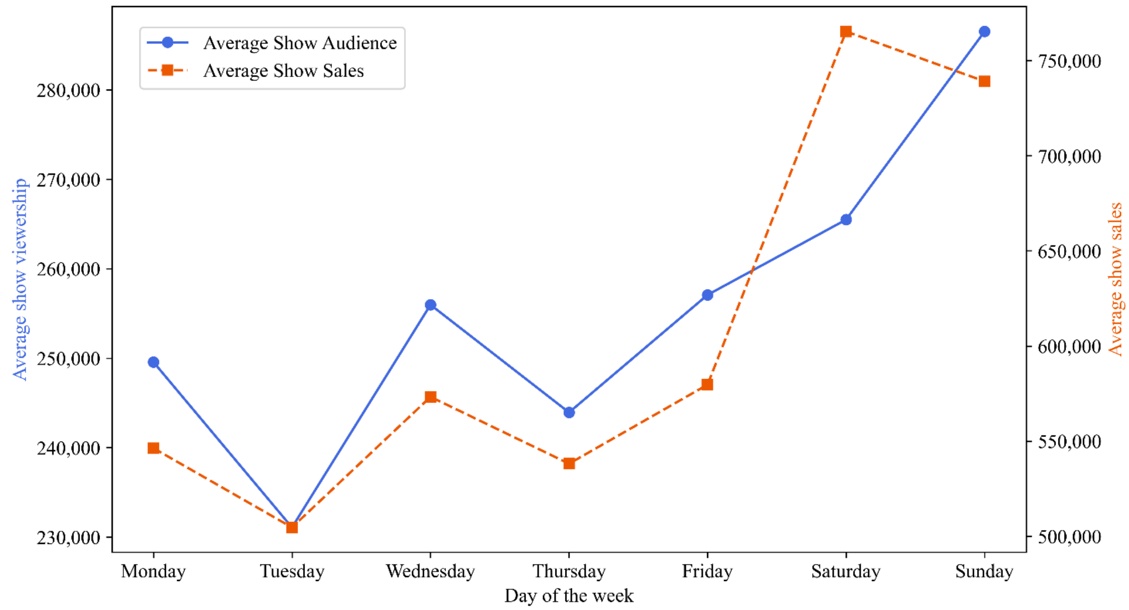
Figure 3.3 The Number of Top Influencers Streaming by Time of Day Over the Nine-Week Period



3.4.2.b. Show outcomes

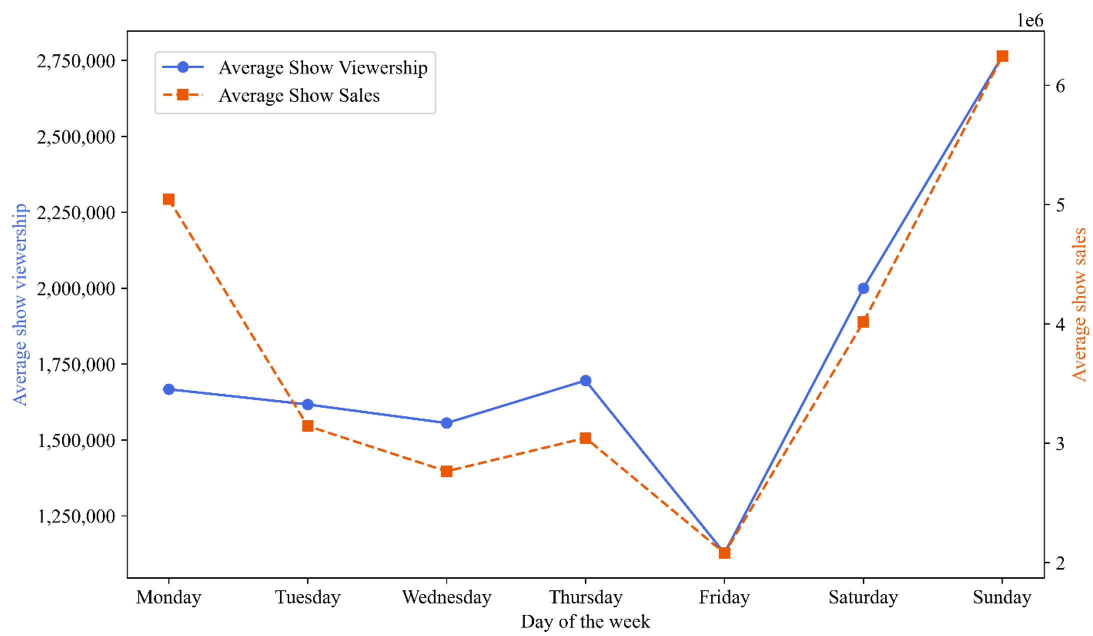
Figure 3.4 and Figure 3.5 present the average viewership and sales per show by day of the week for established influencers and top influencers, respectively. For established influencers, shows on Tuesdays recorded the lowest average viewership and sales. Average viewership increased by over 25% from Tuesday, peaking on Saturday, while average sales peaked on Sunday with more than 50% increase compared to Tuesday. For top influencers, the average viewership and sales amount were the lowest on Friday. Both metrics peaked on Sunday, with viewership more than doubling and sales increasing over threefold compared to Friday.

Figure 3.4 Established Influencers: Average Show Viewership and Show Sales by Day of the Week over the Nine-week Period



Note: The average show sales were in Chinese Yuan (RMB), and the exchange rate was 1 RMB ≈ \$0.15 as of September 2021.

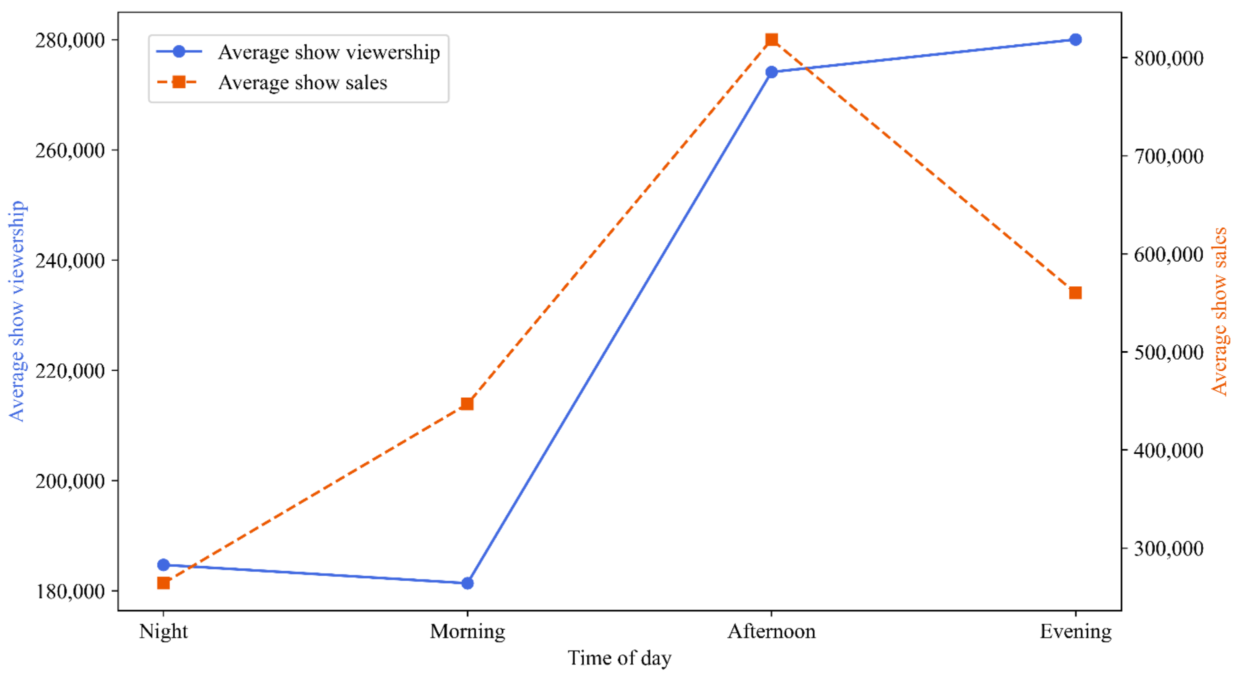
Figure 3.5 Top Influencers: Average Show Viewership And Show Sales by Day of The Week Over the Nine-Week Period



Note: The average show sales were in Chinese Yuan (RMB), and the exchange rate was 1 RMB ≈ \$0.15 as of September 2021.

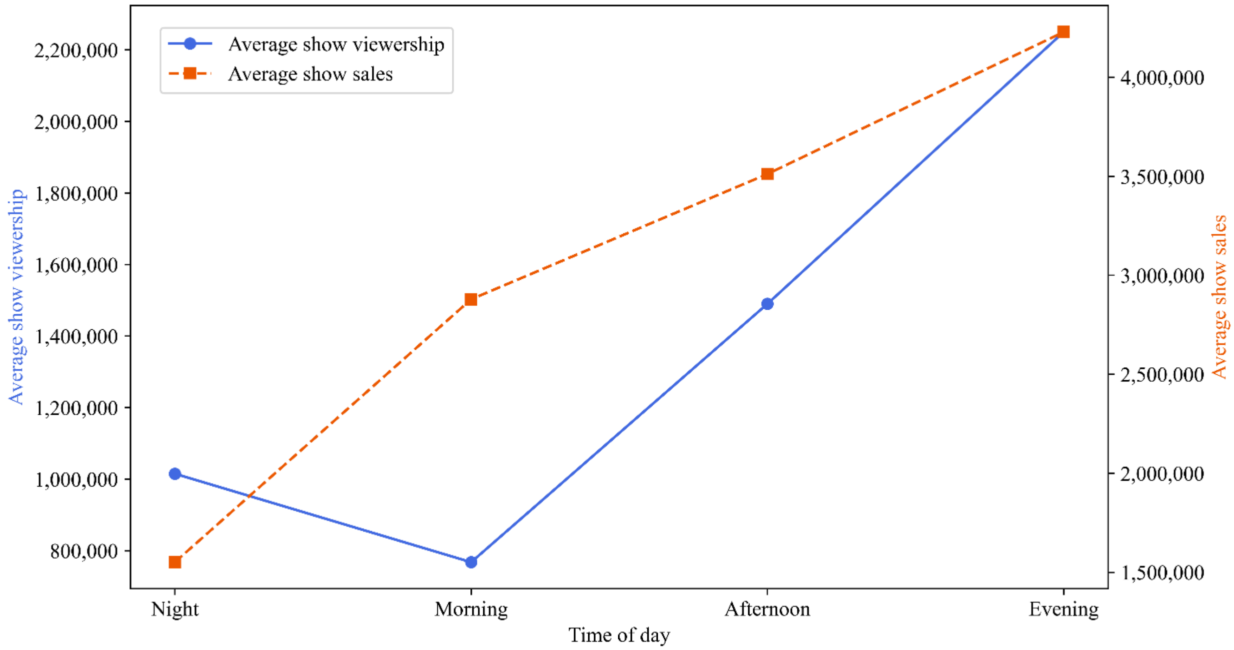
Figure 3.6 and Figure 3.7 demonstrate how average viewership and sales per show vary by time of day for established influencers and top influencers. For established influencers, the average viewership per show was low during the Night and Morning. It increased in the Afternoon and peaked in the Evening, reaching levels 50% higher than those in the Night and Morning. Interestingly, their average sales per show, while lowest during the Night, peaked in the Afternoon rather than the Evening. Specifically, sales in the Afternoon were approximately 2.6 times those in the Night, whereas sales in the Evening were only 1.9 times the Night levels. For top influencers, the average sales per show were lowest during the Night, while the smallest average viewership per show occurred in the Morning. Despite this, shows in the Morning generated nearly twice the sales of those during the Night. Both average viewership and sales per show peaked in the Evening, with peak values exceeding 2.7 times their corresponding minimums.

Figure 3.6 Established Influencers: Average Show Viewership And Show Sales by Time of Day Over The Nine-Week Period



Note: The average show sales were in Chinese Yuan (RMB), and the exchange rate was 1 RMB ≈ $0.15 as of September 2021.

Figure 3.7 Top Influencers: Average Show Viewership And Show Sales by Time of Day Over the Nine-Week Period

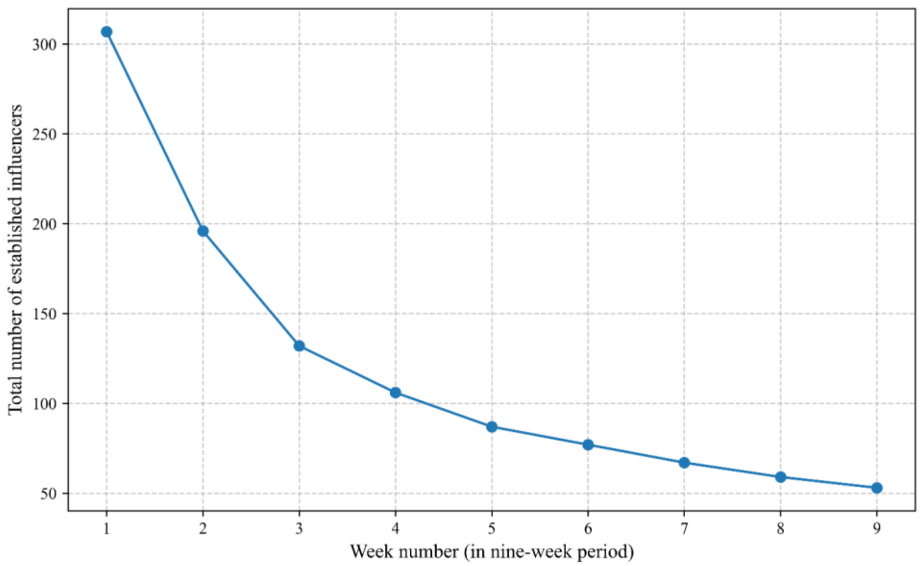


Note: The average show sales were in Chinese Yuan (RMB), and the exchange rate was 1 RMB ≈ $0.15 as of September 2021.

3.4.2.c. Consistency

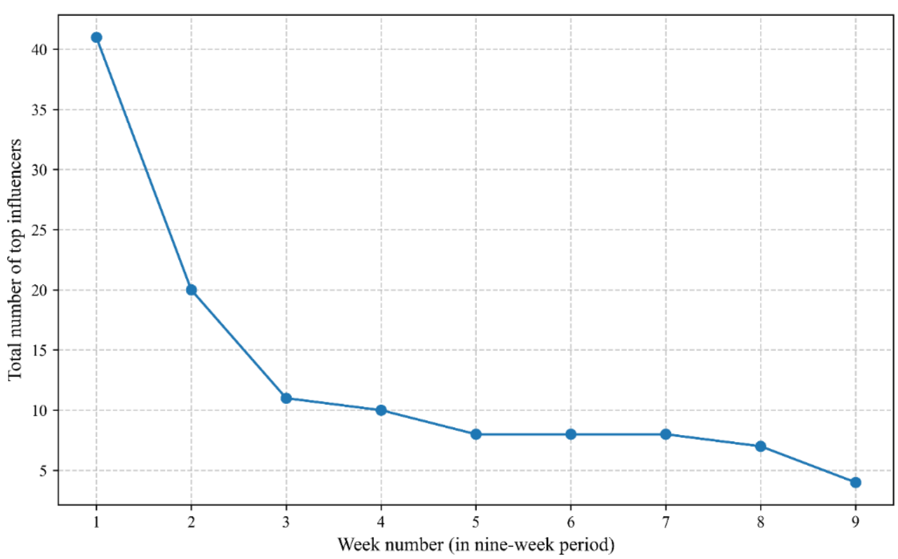
We here present examples to showcase how likely influencers were to maintain consistency in scheduling their shows. Figure 3.8 and Figure 3.9 use the influencers' first show in the data period as a benchmark to calculate how many of them continued streaming on the same day of the week in subsequent weeks. Among the 347 established influencers, approximately 56% of the influencers streamed on the same day of the week in the second week, with this number gradually declining over time. By the end of the nine-week period, only 51 established influencers continued streaming on the same day of the week as their first show. Similarly, around 50% of top influencers streamed consistently on the same day in the second week. However, by the ninth week, only three out of 51 top influencers maintained this pattern.

Figure 3.8 Total Number of Established Influencers Streamed Consistently on the Same Day of the Week



Note: We used the day of the week when influencers first streamed a show in the initial week of the nine-week period as the benchmark. We then compared the shows streamed in subsequent weeks to those in the prior weeks. Finally, we counted the number of established influencers who consistently streamed on the same day each week.

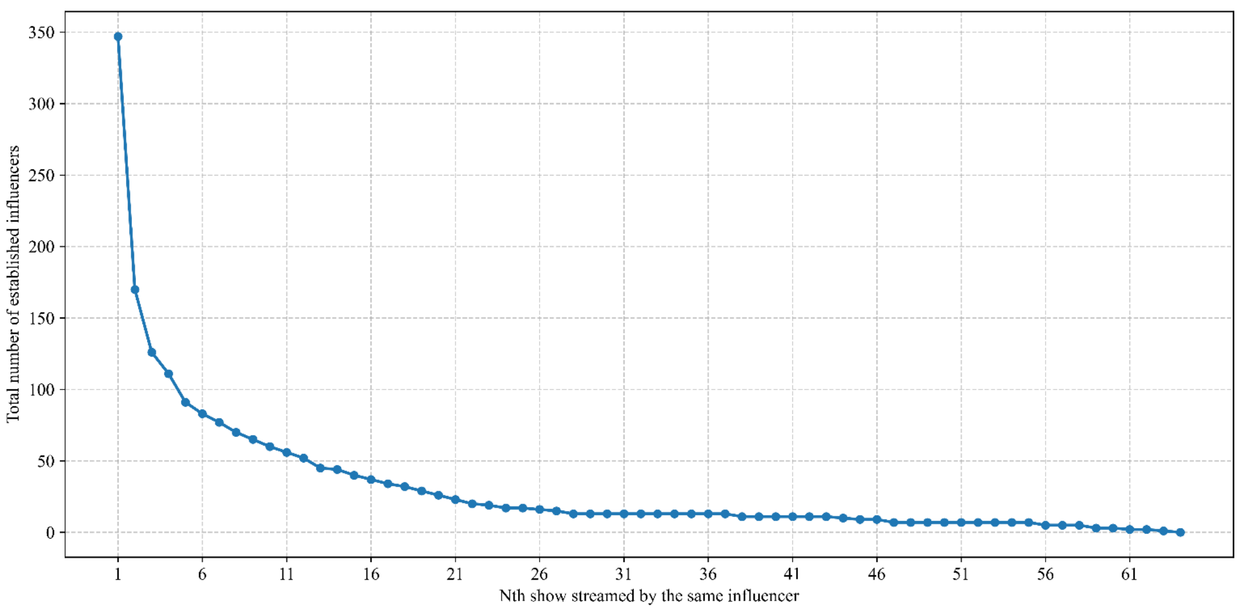
Figure 3.9 Total Number of Top Influencers Streaming Consistently on the Same Day of the Week



Note: We used the day of the week when influencers first streamed a show in the initial week of the nine-week period as the benchmark. We then compared the shows streamed in subsequent weeks to those in the prior weeks. Finally, we counted the number of top influencers who consistently streamed on the same day each week.

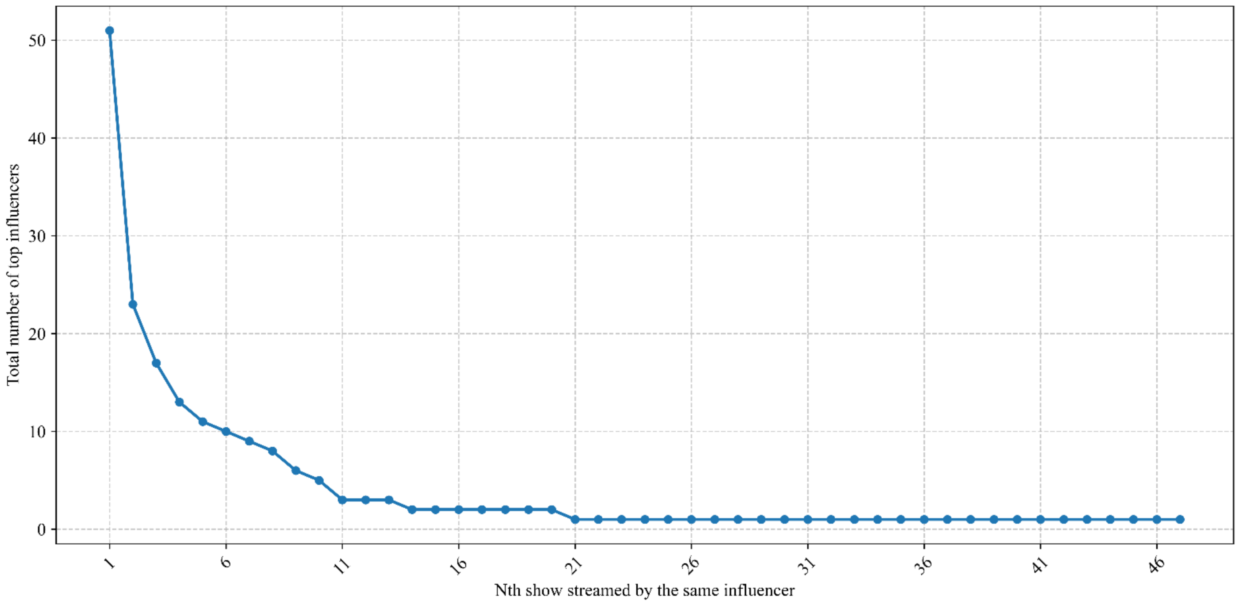
Figure 3.10 and Figure 3.11 use the influencers' first show in the data period as a benchmark to calculate how many of them continued streaming within the same time interval in subsequent shows. Among the 347 established influencers, approximately 50% streamed at the same time interval for their second show, but this percentage declined with each additional show. By the end of the nine-week period, only two established influencers continued streaming within the same time interval as their first show. Similarly, about 50% of the 51 top influencers streamed within the same time interval for their second show. The percentage dropped dramatically afterward, with three top influencers maintaining this pattern for 13 consecutive shows, two for 20 shows, and one for 47 shows.

Figure 3.10 Total Number of Established Influencers Streaming Their Nth Show in the Same Time Interval



Note: N =1 refers to the first show streamed by the influencer over the nine-week period. We used the time interval of the influencers' first show as the benchmark. We then compare the time intervals of subsequent shows to those of prior shows. Finally, we counted the number of established influencers who consistently streamed their Nth show in the same time interval.

Figure 3.11 Total Number of Top Influencers Streaming Their Nth Show in the Same Time Interval



Note: N =1 refers to the first show streamed by the influencer over the nine-week period. We used the time interval of the influencers' first show as the benchmark. We then compare the time intervals of subsequent shows to those of prior shows. Finally, we counted the number of top influencers who consistently streamed their Nth show in the same time interval.

3.5. Methodology

We first examine the impact of the key timing factors — time patterns, spillover effects, and schedule consistency — on show outcomes in livestream shopping.

3.5.1. Key Variables

We measure show outcomes with two dependent variables: show viewership and show sales. $ShowViewership_{itd}$ is defined as the total number of viewers in the show streamed by the influencer i at time interval t on date d, while $ShowSales_{itd}$ measures the total sales amount generated in the show streamed by influencer i at time interval t on date d. Because show viewership and show sales are strictly positive and exhibit high skewness, we apply a logarithmic transformation to account for distributional violations[5].

We use the following independent variables to measure the involved timing factors. The first factor, *time patterns,* is measured in two dimensions: the day of the week and the time of day. To capture day-of-the-week effects, we specify seven indicator variables, $DayofWeek_{itd}$, corresponding to Monday through Sunday, with Sunday serving as the baseline. The respective indicator variable is equal to 1 if a show is streamed by influencer *i* on that day and 0 otherwise. Similarly, we define four indicator variables, $TimeofDay_{itd}$, to capture the time-of-day effects. Each represents the four previously defined time intervals: *Night*, *Morning*, *Afternoon*, and *Evening*. Each indicator variable equals 1 if the majority of influencer i's show duration aligns with a specific time interval and 0 otherwise.

The second factor is *spillover effects.* In this study, we focus on the spillover effects from top influencers and celebrities with over 10 million followers. We define $Spillover_{itd}$, as the total number of top influencers and celebrities whose shows overlapped with the show streamed by the focal influencer *i* during the same time interval *t* on date *d* (See Appendix B for detailed measurement of *spillover effects*).

The third factor is *scheduling consistency*, which is measured using two independent variables. $DayConsistency_{itd}$ is an indicator variable that captures whether influencer *i* streamed on the same day of the prior week (1 = yes, 0 otherwise). $TimeConsistency_{itd}$is an indicator variable that captures whether influencer i streamed the show within the same time interval *t* as their most recent preceding show (1 = yes, 0 otherwise). We detail the measurement of *scheduling consistency* with examples in Appendix B.

[5] We add one before taking the log transformation to prevent taking the log of negative values.

We include several control variables to account for show-level heterogeneity and seasonality. First, we control for the length of the show (in seconds) with the variable, $ShowDuration_{itd}$, and the varieties of products sold in the show with the variable, $ProductVariety_{itd}$, as the length of the show and product variety may affect show outcomes. We take the natural logarithm of each variable to reduce the distributional violation. Second, we control for seasonality by including week-of-year dummies to capture the unobserved heterogeneity that might affect show outcomes in different weeks (e.g., shifts in external shopping trends or market conditions). In addition, holidays may also affect the show outcomes; we include holiday dummies to account for the impact of National Day holidays (i.e., October 1st to October 7th) in China. The operationalization of these variables is summarized in Table 3.2.

Table 3.2 Variable Operationalization

Category	**Variable**	**Measurement**
Dependent variables	log ($ShowViewership_{itd}$)	Natural logarithm of the total number of viewers in the show streamed by influencer *i* during time interval *t* on date *d*
	log ($ShowSales_{itd}$)	Natural logarithm of the total sales amount in the show streamed by influencer *i* during time interval *t* on date *d*.
	$Livestream_{itd}$	Coded as 1 if influencer *i* streamed a show during time interval *t* on date *d*, and 0 otherwise
Independent variables	$DayofWeek_{itd}$	1 to 7 represent Monday to Sunday, respectively
	$TimeofDay_{itd}$	1 to 4 represent Night, Morning, Afternoon, and Evening, respectively
	$DayConsistency_{itd}$	Coded as 1 if influencer *i* streamed a show on the same day *d* in the prior week between September 13 and November 7, 2021, and 0 otherwise
	$TimeConsistency_{itd}$	Coded as 1 if influencer *i* streamed a show during the same time interval *t* as the last preceding show between September 13 and November 7, 2021, and 0 otherwise
	$Spillover_{itd}$	The number of top influencers and celebrities who streamed shows that are overlapping with the focal influencer

		i during time interval *t* on date *d* between September 13 and November 7, 2021
	$ExpectedSpillover_{itd}$	The number of top influencers and celebrities who streamed shows during time interval t on the same day of the prior week between September 13 and November 7, 2021
Control variables	log ($ProductVariety_{itd}$)	Natural logarithm of the varieties of products sold in the show streamed by influencer *i* during time interval *t* on date d
	log ($ShowDuration_{itd}$)	Natural logarithm of total length (in seconds) of a show streamed by influencer *i* during time interval *t* on date d
	$HolidayDummy_{id}$	Coded as 1 if the show date falls between Oct 1, and Oct 7, 2021, and 0 otherwise
	$WeekDummy_{id}$	1 to 9 represent the nine weeks in the dataset, respectively

Table 3.3 presents the descriptive statistics of variables, and Table 3.4 provides the correlation among the key variables. The high variance for variables, *ShowViewership* and *ShowSales*, supports the log transformation of these two dependent variables in our model. In addition, the average and maximum Variance Inflation Factor (VIF) values are 1.68 and 2.51 for top influencers, and 1.73 and 2.67 for established influencers. This indicates that multicollinearity is not a concern.

Table 3.3 Descriptive Statistics

N = 17,732 (September 6–November 7, 2021)				
	Mean	SD	Min	Max
ShowViewership	378,352	1,278,127	452	33,658,745
log (ShowViewership)	11.75	1.38	6	17
ShowSales	856,698	4,634,463	1	209,922,752
log (ShowSales)	11.82	–	1	19
Monday	0.14	–	0	1
Tuesday	0.14	–	0	1
Wednesday	0.16	–	0	1
Thursday	0.15	–	0	1
Friday	0.14	–	0	1
Saturday	0.13	–	0	1
Sunday	0.14	–	0	1

Night (0:00-5:59)	0.05	−	0	1
Morning (6:00-11:59)	0.18	−	0	1
Afternoon (12:00-17:59)	0.31	−	0	1
Evening (18:00-23:59)	0.46	−	0	1
ProductVariety	36	32	1	414
log (ProductVariety)	3.20	1.02	1	6
ShowDuration	12,489	8,319	1,808	60,390
log (Show Duration)	9.24	0.63	8	11

Table 3.4 Variable Correlation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) log(ShowViewership)	1.000														
(2) log(ShowSales)	0.739*	1.000													
(3) Monday	-0.008	-0.014	1.000												
(4) Tuesday	-0.016*	-0.013	-0.162*	1.000											
(5) Wednesday	0.004	0.009	-0.170*	-0.176*	1.000										
(6) Thursday	-0.002	-0.003	-0.168*	-0.173*	-0.181*	1.000									
(7) Friday	-0.016*	-0.011	-0.163*	-0.168*	-0.176*	-0.174*	1.000								
(8) Saturday	-0.002	-0.001	-0.156*	-0.161*	-0.169*	-0.166*	-0.161*	1.000							
(9) Sunday	0.041*	0.032*	-0.157*	-0.162*	-0.170*	-0.167*	-0.162*	-0.155*	1.000						
(10) Night	-0.054*	-0.085*	-0.002	-0.005	0.005	-0.006	0.010	-0.007	0.006	1.000					
(11) Morning	-0.130*	-0.046*	-0.001	0.011	-0.005	0.000	0.001	-0.003	-0.003	-0.106*	1.000				
(12) Afternoon	-0.046*	-0.007	-0.006	-0.010	0.006	0.000	-0.002	0.014	-0.003	-0.152*	-0.311*	1.000			
(13) Evening	0.166*	0.079*	0.007	0.003	-0.004	0.002	-0.004	-0.008	0.003	-0.213*	-0.434*	-0.620*	1.000		
(14) log(ProductVariety)	0.135*	0.356*	-0.012	-0.003	0.003	0.001	-0.013	0.013	0.011	-0.041*	-0.048*	0.060*	-0.001	1.000	
(15) log(ShowDuration)	0.342*	0.490*	-0.006	-0.027*	0.006	-0.005	-0.002	0.017*	0.017*	-0.129*	0.010	0.097*	-0.042*	0.349*	1.000

**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

3.5.2. Model Specification

We test the impact of key timing factors on show outcomes. To account for influencers' time-invariant unobserved characteristics, we adopt the fixed effects model for panel data. This specification also allows the arbitral correlations between the unobserved factors and the main independent variables (Wooldridge, 2010). We thus specify the model as follows:

$$\log(ShowViewership_{itd}) = \alpha_i + \beta_0 + \sum_{n=1}^{n=6} \beta_n DayofWeek_{itd} + \sum_{n=7}^{n=9} \beta_n TimeofDay_{itd} + \beta_{10} Spillover_{itd} + \beta_{11} DayConsistency_{itd} + \beta_{12} TimeConsistency_{itd} + \beta_{13} \log(ProductVariety_{itd}) + \beta_{14} \log(ShowDuration_{itd}) + \sum_{n=15}^{n=22} \beta_n WeekDummy_{id} + \beta_{23} HolidayDummy_{id} + \epsilon_{itd} \quad (1)$$

$$\log(ShowSales_{itd}) = \alpha_i + \beta_0 + \sum_{n=1}^{n=6} \beta_n DayofWeek_{itd} + \sum_{n=7}^{n=9} \beta_n TimeofDay_{itd} + \beta_{10} Spillover_{itd} + \beta_{11} DayConsistency_{itd} + \beta_{12} TimeConsistency_{itd} + \beta_{13} \log(ProductVariety_{itd}) + \beta_{14} \log(ShowDuration_{itd}) + \sum_{n=15}^{n=22} \beta_n WeekDummy_{id} + \beta_{23} HolidayDummy_{id} + \epsilon_{itd} \quad (2)$$

α_i is the fixed effect of an influencer capturing unobserved individual heterogeneity. β_1 to β_6 capture the day-of-the-week effects on show outcomes (with *Sunday* as the baseline); β_7 to β_9 capture the time-of-day effects on show outcomes (with *Evening* as the baseline). β_{10} captures the impact of spillover on show outcomes; β_{11} and β_{12} capture the effects of scheduling consistency on show outcomes. β_{13} to β_{23} capture the effects of control variables. To differentiate the impact of timing factors on shows hosted by top influencers and established influencers, we run separate regressions for each influencer group.

3.5.3. Controlling for Potential Endogeneity

Despite the control variables included in our regression model, unobservable factors may still influence both scheduling consistency and show outcomes. For instance, influencers might maintain consistent schedules based on unobserved market knowledge, such as their experience or insights into industry trends. This tendency could bias the estimated effects of scheduling consistency, measured by $DayConsistency_{itd}$ and $TimeConsistency_{itd}$. To address this potential endogeneity issue, we employ the two-stage least squares (2SLS) approach. First, we construct instrumental variables that could satisfy the two criteria: relevance and exclusion restrictions, such that they correlate with $DayConsistency_{itd}$ and $TimeConsistency_{itd}$, but not correlate with the error term (i.e., do not directly affect show viewership and sales). Second, we use these instruments to predict the endogenous regressors and substitute the predicted values into the response model (Wooldridge, 2010).

To construct an instrumental variable for $DayConsistency_{itd}$, we use the number of days the focal influencer streamed on the same day over the prior four weeks. This instrument is expected to exhibit a strong correlation with day consistency, as influencers likely reference their previous scheduling patterns when deciding whether to maintain day consistency. At the same time, the day recurrence count in the previous four weeks is unlikely to directly influence current show outcomes, which are primarily driven by contemporaneous factors.

For $TimeConsistency_{itd}$, we use the number of times the focal influencer streamed during the same time interval in the prior week as an instrumental variable. This instrument is relevant because influencers who regularly streamed in the same time interval in the prior week are more likely to maintain time consistency. At the same time, the time interval recurrence count in the previous week is unlikely to directly affect current show outcomes, which are primarily driven by contemporaneous factors(See Appendix B for detailed measurements and examples of two instrumental variables)

To demonstrate the relevance of our instrumental variables, we report the estimation of the first-stage equations in Appendix B. The significant coefficient estimates of the first-stage equation confirm the strong relevance of both instruments.

3.6. Results

We estimate Eq.(1) and Eq.(2) separately for established influencers and top influencers. We report the main estimation results for the fixed effects model with instruments in Table 3.5 (The results without endogeneity correction are reported in Appendix B). Columns (1) and (2) present the results for established influencers, while columns (3) and (4) correspond to top influencers. All the standard errors are clustered at the influencer level to account for influencer-show observations' correlation across periods.

3.6.1. Time Patterns

For established influencers, in column (1) in Table 3.5, the coefficients of day indicator variables and time indicator variables are negative and significant. This indicates that show viewership is lower on any other day compared to Sundays and lower in any other time interval compared to the evening. These results are consistent with H1 and H2, which state that the show outcomes are better on the weekend and in the evening. Column (2) in Table 3.5 indicates show sales are, on average, 7.1% and 7% lower on *Wednesday* ($\beta = -0.071, p < 0.05$) and *Thursday* ($\beta = -0.07, p < 0.05$) compared to the sales generated on *Sunday*; Show sales are 8.8% lower in the *Afternoon* ($\beta = -0.088, p < 0.10$) compared to the *Evening*[6]. For top influencers, column (3) of Table 3.5 demonstrates that, on average, show viewership is 11.2% lower on *Wednesday* ($\beta = -0.112, p < 0.01$) compared to *Sunday*, and 23.3% lower in the *Morning* ($\beta = -0.233, p < 0.01$) compared to the *Evening*. In column (4) of Table 3.5, the coefficients of the main independent variables are not statistically significant, suggesting that time patterns have no significant impact on show sales for top influencers. These findings further highlight that the impact of timing factors on show outcomes differs between established and top influencers.

3.6.2. Spillover Effects

Interestingly, for established influencers, the coefficients for *Spillover* in columns (1) and (2) of Table 3.5 are both positive and significant, rejecting hypothesis H3. In other words, contrary to our hypothesis that the spillover effects weaken the established influencers' show outcomes, top influencers and celebrities exert a positive and significant impact on established influencers' show viewership ($\beta = 0.005, p < 0.05$) and show sales ($\beta = 0.007, p < 0.05$). Specifically, when an additional top influencer or celebrity streams at the same time as an established influencer, the focal established influencer's show viewership averagely increases by 0.5% (i.e., $e^{0.005} - 1$), and show sales rise by 0.7% (i.e., $e^{0.007} - 1$), holding everything else constant. At first glance, the magnitude seems relatively modest. However, a back-of-the-envelope calculation suggests that one additional top influencer or celebrity leads to an average increase of approximately 1,892 viewers and RMB 5,997[7]. For top influencers, the estimates in columns (3) and (4) show that the impact of spillover effects on show outcomes is not significant, supporting H4.

[6] This result contrasts with the model-free evidence shown in Fig. 3(a) and Fig. 4(a), which demonstrate that the established influencers had highest average show sales on Saturday, and in the Afternoon respectively. This discrepancy arises because show durations tend to be longer on Saturdays and in the Afternoon. Controlling for show duration provides more precise estimates of day-of-the week and time-of-day effects.

[7] This calculation is based on the average viewership and show sales reported in summary statistics in Table 3. The average viewership was 378,352, and the estimated increase of viewers was calculated as 378,352*0.5% ≈1,892.

These findings indicate that established influencers need not worry that top influencers and celebrities streaming concurrently will divert their viewers. Instead, top influencers or celebrities bring a significant influx of new viewers to the platform, who are likely to explore other ongoing livestreams. However, it remains unclear why these new viewers do not similarly benefit other top influencers to the same extent. A potential explanation is that top influencers share highly overlapping audience pools, whereas the audiences of established and top influencers are more distinct. Further research is expected to investigate this phenomenon.

3.6.3. Scheduling Consistency

For both established and top influencers, the coefficients of *DayConsistency* and *TimeConsistency* are not significant, suggesting that scheduling consistency has no significant impact on show outcomes. This finding contradicts hypotheses H5 and H6, which propose that scheduling consistency improves show performance. One possible explanation is that influencers maintain a consistent schedule to enhance customer loyalty and foster habitual viewing over time. Nonetheless, the impact of this practice on show outcomes appears to be negligible.

3.6.4. Robustness Check

We conduct robustness checks to assess the validity of our findings. First, we replicate our results using the fixed effects model with instrumental variables with additional diagnostic tools (Schaffer, 2005). The results are reported in Appendix B. Second, beyond show sales amount, show performance can also be evaluated by the quantity of products sold during the show. This allows us to isolate the effect of price per unit since top influencers may sell products with relatively higher unit prices, which may inflate the total sales amount. We conduct additional

Similarly, the average show sales were RMB 856,698, with an estimated increase of 856,698*0.7% ≈ RMB 5,997, which was approximately USD 930 at an exchange rate of 0.155 in September 2021.

analysis on the impact of timing factors on sales quantity and present the model specification and results in Appendix B. These additional analyses yield robust results.

Table 3.5 Main Estimation Results with Instruments for Show Outcomes Model

	Established influencers		**Top influencers**	
	(1)	(2)	(3)	(4)
Variables	Log(ShowViewership)	Log(ShowSales)	Log(ShowViewership)	Log(ShowSales)
Monday	-.023*	-.021	-.041	-.001
	(.013)	(.026)	(.045)	(.126)
Tuesday	-.033**	-.037	-.048	-.004
	(.013)	(.031)	(.042)	(.114)
Wednesday	-.074***	-.071**	-.112***	-.135
	(.014)	(.032)	(.036)	(.145)
Thursday	-.067***	-.07**	-.025	.059
	(.014)	(.031)	(.044)	(.148)
Friday	-.041***	-.024	-.05	-.092
	(.013)	(.025)	(.041)	(.137)
Saturday	-.03**	-.044	-.001	-.193
	(.012)	(.029)	(.039)	(.189)
Night	-.142**	.011	-.282	-.359
	(.056)	(.104)	(.208)	(.327)
Morning	-.23***	.048	-.233***	-.218
	(.044)	(.083)	(.072)	(.23)
Afternoon	-.167***	-.088*	-.068	-.094
	(.031)	(.05)	(.069)	(.173)
Spillover	.005**	.007**	.005	.001
	(.002)	(.003)	(.004)	(.007)
DayConsistency	.002	.051	-.105	.046
	(.049)	(.081)	(.097)	(.146)
TimeConsistency	.054	.011	.001	-.128
	(.075)	(.14)	(.17)	(.368)
Log(ShowDuration)	1.033***	1.348***	1.079***	1.376***
	(.032)	(.057)	(.048)	(.163)
Log(ProductVariety)	.039	.475***	.006	1.105***
	(.028)	(.077)	(.03)	(.354)
Constant	2.004***	-2.34***	3.105***	-3.433***
	(.249)	(.457)	(.396)	(.956)
Observations	14,454	14,454	1,257	1,257
Pseudo R^2	0.594	0.454	0.662	0.590
Week Dummy	Yes	Yes	Yes	Yes
Holiday Dummy	Yes	Yes	Yes	Yes

Standard errors in parentheses are clustered at the influencer level.
**** p<.01, ** p<.05, * p<.1*

3.7. Empirical Study on Influencers' Timing Decisions

Thus far, we have established the theoretical framework that links the key timing factors to influencers' show outcomes. Our empirical findings reveal distinct time patterns for both established and top influencers. The results show that established influencers benefit from spillover effects from top influencers and celebrities, while top influencers do not. Additionally, the findings indicate that scheduling consistency does not enhance show outcomes. Presumably, influencers, aware of these insights, should incorporate them into their timing decisions. In this section, we examine how established and top influencers account for these timing factors in their scheduling strategies.

To empirically examine influencers' timing decisions, we specify a logit model with fixed effects for panel data, given that the dependent variable, $Livestream_{itd}$, is a binary variable that indicates whether influencer *i* live-streamed during time interval *t* on date *d*. This approach also avoids the need to estimate additional parameters associated with individual fixed effects (i.e., influencer-specific fixed effects) in a non-linear model (Woodridge, 2010).

We use time patterns (i.e., $DayofWeek_{itd}$ and $TimeofDay_{itd}$), scheduling consistency (i.e., $DayConsistency_{itd}$ and $TimeConsistency_{itd}$), and expected spillover effects as the main independent variables. Since influencers rely on historical data to predict the spillover effects they may encounter at their expected streaming time, we measure the expected spillover effects using $ExpectedSpillover_{itd}$. This variable captures the number of top influencers and celebrities who streamed during the same time interval *t* on the same day of the previous week (See Table 2 for a summary of the variable operationalization). We specify the main estimation equation for influencer *i's* timing decision as follows:

$$Livestream_{itd} = \begin{cases} 1 & if\ Livestream^{*}_{itd} > 0, \\ 0 & Otherwise \end{cases}$$

Where $Livestream^{*}_{itd}$ is a latent variable, which is specified as:

$$Livestream^{*}_{itd} = \sum_{n=1}^{n=6} b_n DayofWeek_{itd} + \sum_{n=7}^{n=9} b_n TimeofDay_{itd} + b_{10} ExpectedSpillover_{itd} + b_{11} DayConsistency_{itd} + b_{12} TimeConsistency_{itd} + c_i + \epsilon_{itd}$$

with

$$Pr(Livestream_{itd} = 1 | \mathrm{X}) = \Lambda\left(\sum_{n=1}^{n=6} b_n DayofWeek_{itd} + \sum_{n=7}^{n=9} b_n TimeofDay_{itd} + b_{10} ExpectedSpillover_{itd} + b_{11} DayConsistency_{itd} + b_{12} TimeConsistency_{itd} + c_i\right) \quad (3)$$

b_1 to b_6 capture the day-of-the-week effects on timing decisions (with *Sunday* as the baseline), while b_7 to b_9 capture the time-of-day effects on timing decisions (with *Evening* as the baseline). b_{10} captures the impact of spillover effects in the prior week on influencers' timing decisions. b_{11} and b_{12} capture the effects of day consistency and time consistency, respectively. c_i controls for influencer-specific fixed effects, and ϵ_{itd} denotes independent error terms.

To differentiate the impact of key timing factors on timing decisions between established and top influencers, we estimate Eq (3) separately for each influencer group.

3.7.1. Estimation Results

The estimation results are presented in Table 3.6. For a clear interpretation of the logit model with fixed effects, we include both the coefficients and the corresponding odds ratio. Specifically, columns (1) and (2) display the estimated coefficients and odds ratios for established influencers, while columns (3) and (4) present the results for top influencers.

3.7.1.a. Time patterns

For established influencers, column (1) of Table 3.6 demonstrates that the coefficients of *Tuesday*, *Wednesday*, *Thursday*, and *Friday* are significantly positive, while the coefficients for *Night, Morning,* and *Afternoon* are significantly negative. Column (2) shows the corresponding odds ratios. Compared to Sunday, established influencers are more likely to stream shows on weekdays except Monday. In addition, they are more likely to stream shows during the *Night* than any other time intervals. As column (3) shows, for top influencers, the coefficients for *Monday*, *Friday*, and *Saturday* are significantly negative, and those for *Night, Morning,* and *Afternoon* are also significantly negative. Column (4) indicates that top influencers are more likely to stream on Sunday and during the evening. These results suggest that established influencers and top influencers have different preferences for the day of the week, but both prefer to stream during the night. One possible explanation is that established influencers may consider livestreaming as a structured job and prefer to stream during weekdays instead of weekends.

3.7.1.b. *Spillover Effects*

As shown in columns (1) and (2) of Table 3.6, the coefficient of spillover effects is significantly negative, with an odds ratio of 0.991, indicating a negative impact on established influencers' timing decisions. Specifically, each additional top influencer or celebrity streaming in the same time interval on the same day of the prior week decreases an established influencer's likelihood of streaming at the same time in the current week by 0.9% (i.e., 1-0.991). This suggests that established influencers tend to avoid scheduling their shows concurrently with top influencers or celebrities. This finding aligns with practitioner insights that influencers deliberately avoid streaming concurrently with top influencers or celebrities to prevent losing viewers. However, for top influencers, we do not find conclusive evidence that the spillover effects from other top influencers or celebrities influence their timing decisions. A potential explanation is that top influencers have no strong preference, as their popularity is comparable.

Table 3.6 Main Estimation Results for Timing Decision Model

	Established influencers		**Top influencers**	
	(1)	(2)	(3)	(4)
Variables	Coefficients	Odds ratios	Coefficients	Odds ratios
Monday	0.0191	1.019	–0.220*	0.802*
	(0.0434)	(0.0443)	(0.134)	(0.107)
Tuesday	0.128***	1.137***	0.0549	1.056
	(0.0424)	(0.0482)	(0.127)	(0.134)
Wednesday	0.273***	1.314***	0.0753	1.078
	(0.0420)	(0.0552)	(0.127)	(0.137)
Thursday	0.225***	1.252***	0.0164	1.017
	(0.0421)	(0.0527)	(0.128)	(0.130)
Friday	0.127***	1.135***	–0.304**	0.738**
	(0.0431)	(0.0489)	(0.136)	(0.100)
Saturday	0.0239	1.024	–0.394***	0.675***
	(0.0438)	(0.0449)	(0.139)	(0.0940)
Night	–2.776***	0.0623***	–3.307***	0.0366***
	(0.0733)	(0.00457)	(0.256)	(0.00936)
Morning	–1.429***	0.239***	–1.792***	0.167***
	(0.0543)	(0.0130)	(0.175)	(0.0291)
Afternoon	–0.718***	0.488***	–0.751***	0.472***
	(0.0373)	(0.0182)	(0.112)	(0.0529)
ExpectedSpillover	–0.00887*	0.991*	–0.00634	0.994
	(0.00485)	(0.00480)	(0.0145)	(0.0144)
DayConsistency	0.351***	1.421***	0.248***	1.282***
	(0.0281)	(0.0399)	(0.0833)	(0.107)
TimeConsistency	1.730***	5.638***	0.959***	2.609***
	(0.0243)	(0.137)	(0.0778)	(0.203)
Observations	77,728	77,728	11,424	11,424
Number of influencers	347	347	51	51

Standard errors are in parentheses.
**** p<.01, ** p<.05, * p<.1*
Columns (1) and (3) provide the estimates of the coefficients for the logit model with fixed effects, and columns (2) and (4) provide the odd ratio of the estimates.

3.7.1.c. Scheduling Consistency

Interestingly, the empirical results reveal a strong tendency for both established and top influencers to maintain consistency in their scheduling. As column (2) of Table 3.6 shows, established influencers are 42.1% more likely to stream on the same day as the prior week than on a different day and are 4.638 times more likely to stream in the same time interval as their previous show than a different time interval. Similarly, column (4) indicates that top influencers are 28.2% more likely to be on the same day as the prior week and 1.609 times more likely to stream during the same time interval. These findings also align with practitioners' recommendations that influencers should maintain a consistent schedule to demonstrate their commitment and build a regular audience base (StreamLadder, n.d.).

3.8. Discussion: Discrepancies Between Influencers' Timing Decisions and Show Outcomes

The empirical analysis of influencer timing decisions reveals that three key timing factors—time patterns, spillover effects, and scheduling consistency—play a crucial role in how influencers schedule their shows. However, influencers' considerations of these factors do not fully align with their actual impact on show outcomes. In fact, there are intriguing discrepancies between the effects of these factors on show outcomes and influencers' timing decisions, as highlighted in Table 3.7.

Table 3.7 Summary of Key Findings

(a) Established Influencers

		Show outcomes	Timing decisions
Time patterns	Day of the week	**Show outcomes peak on Sunday**	**Prefer streaming on weekdays, except Monday**
	Time of day	Show outcomes peak in the evening	Prefer streaming in the evening
Spillover effects		**Top influencers and celebrities create positive spillover effects**	**Prefer not streaming simultaneously with top influencers or celebrities**
Scheduling consistency	Day consistency	**Scheduling shows on the same day does not improve show outcomes**	**Prefer streaming on the same day**
	Time consistency	**Scheduling shows in the same time interval does not improve show outcomes**	**Prefer streaming in the same time interval**

(b) Top Influencers

		Show outcomes	Timing decisions
Time patterns	Day of the week	**Viewership is low on Wednesday**	**Prefer not streaming on Monday, Friday and Saturday**
	Time of day	Show outcomes peak in the evening	Prefer streaming in the evening
Spillover effects		Other top influencers and celebrities do not generate significant spillover effects	Do not care if streaming simultaneously with other top influencers or celebrities
Scheduling consistency	Day consistency	**Scheduling shows on the same day does not improve show outcomes**	**Prefer streaming on the same day**
	Time consistency	**Scheduling shows in the same time interval does not improve show outcomes**	**Prefer streaming in the same time interval**

The discrepancies primarily fall into three areas. First, influencers do not always follow time patterns when scheduling their shows. Established influencers attract larger viewership and generate higher sales in the shows streamed on Sundays, yet they prefer streaming on weekdays. Top influencers avoid streaming on Mondays, Fridays, and Saturdays, even though show viewership and sales on these days are comparable to other days. Second, established influencers appear to misinterpret the spillover effects from top influencers and celebrities. They attempt to avoid streaming simultaneously with too many top influencers and celebrities, even though the presence of these popular influencers actually attracts significant additional viewers and boosts sales. Third, both established and top influencers have a strong tendency to maintain scheduling consistency. However, this effort does not improve show outcomes in terms of either viewership or sales.

These discrepancies may stem from three potential reasons.

Neglected operational costs When influencers schedule their shows to maximize show outcomes, they may also consider operational constraints and costs which are latent in the dataset. For example, many established influencers may treat live streaming as a structured job, preferring to work on weekdays rather than weekends, even though streaming on Sundays yields higher viewership and sales. The opportunity cost of working on Sundays may outweigh the expected benefits. Similarly, influencers may favor a consistent streaming schedule not to foster demand loyalty but to streamline their workflow, optimize personal work-life balance, and minimize uncertainty in their operations (Kesavan et al.; Lu et al., 2022; Johnson, 2011).

Prioritizing long-term growth over immediate gains Influencers may also base their timing decisions on long-term strategic goals rather than short-term show outcomes. A consistent streaming schedule, for instance, may not immediately boost viewership or sales but can contribute to building a loyal audience base over time. Research in marketing and consumer behavior suggests that habitual engagement leads to stronger brand loyalty and customer retention (Dwivedi, 2015; Dessart et al., 2019; De Villiers, 2015; Helme-Guizon & Magnoni, 2019). By adhering to a predictable streaming schedule, influencers may gradually convert casual viewers into dedicated followers, ultimately enhancing long-term profitability. This approach mirrors the strategies of content creators on platforms like YouTube and Twitch, where a consistent posting schedule is often associated with higher audience retention and community engagement.

Market misconceptions and cognitive biases Since livestream shopping is a relatively new business model, influencers may hold inaccurate perceptions about the market, leading to suboptimal timing decisions. They might misjudge the effects of time patterns, overestimate the importance of schedule consistency, or, most critically, misunderstand the role of top influencers and celebrities. Rather than recognizing the mutual benefits of coexisting with top influencers or celebrities, some may perceive them as direct competitors and avoid streaming simultaneously, despite evidence that top influencers and celebrities generate positive spillover effects.

A striking real-world example is the case of Viya, one of the most prominent livestream influencers in China. In December 2021, when Viya was temporarily banned from the market due to legal issues, many business practitioners anticipated that her departure would redistribute her audience to other influencers. However, the opposite occurred—her absence led to a substantial decline in total sales across the platform, reducing overall market prosperity (Sina Finance, 2021). This suggests that top influencers do not merely compete for viewers but also attract and expand the total audience base, benefiting the entire ecosystem. The failure to recognize such interdependencies may explain why many influencers hesitate to schedule shows alongside industry leaders, despite the potential advantages.

These three concerns —operational cost considerations, long-term strategic thinking, and market misconceptions—offer plausible explanations for why influencers' timing decisions deviate from the patterns that would maximize immediate show outcomes. Understanding these underlying motivations provides valuable insights for both influencers and platform managers seeking to optimize scheduling strategies in the evolving livestream shopping landscape.

3.9. Conclusion

3.9.1. Theoretical Contributions

Livestream shopping is a rapidly growing business model that offers consumers a condensed and immersive online shopping experience. Unlike conventional e-commerce, where transactions occur anytime, this time-sensitive retail format is highly dependent on strategic timing.

To our best knowledge, this study is the first to examine strategic timing decisions in the livestream shopping market. We identify key timing trends among influencers and introduce a theoretical framework with three main drivers of timing decisions: time patterns, spillover effects, and scheduling consistency. We empirically test this framework using livestream shopping data, investigating how these factors influence both show outcomes and influencers' scheduling choices. The findings underscore the critical role of timing in livestream shopping and the key factors in influencers' scheduling decisions, paving the way for future marketing research on this emerging yet underexplored topic.

Our empirical analysis also sheds light on the nature of the livestream shopping market. The observed time patterns reveal peak and off-peak days and hours for both established and top influencers, highlighting similarities and differences between livestream shopping platforms and traditional social media markets. The positive spillover effects from top influencers and celebrities underscore the symbiotic relationship between top influencers and livestream platforms, emphasizing their unique value in expanding platform-wide viewership and sales. These findings provide important insights into the operational and competitive dynamics of livestream shopping.

Furthermore, our analysis clarifies influencers' timing decisions and uncovers notable discrepancies between the impact of key timing factors on scheduling choices and their actual effect on show performance. This study makes a significant contribution to the growing literature on strategic timing decisions—an increasingly important marketing factor. While our results align with existing research identifying time patterns, spillover effects, and scheduling consistency as major drivers of sellers' timing decisions, the observed discrepancies suggest that these decisions are far more complex than previously understood. Influencers may balance peak demand with operational constraints, immediate returns with long-term customer loyalty, and competitive positioning with market uncertainty. Future research should further explore the underlying intentions and decision-making processes behind timing strategies in livestream shopping.

3.9.2. Managerial Implications

Our study provides valuable insights into the strategic role of timing in the livestream shopping market, offering practical implications for influencers and platform managers seeking to optimize scheduling strategies.

First, our findings present a comprehensive view of how timing factors influence show viewership and sales, as well as influencers' scheduling decisions. These insights enable business practitioners to make data-driven scheduling decisions that align peak demand with other constraints. Importantly, there is no one-size-fits-all timing strategy; Influencers should tailor their scheduling choices to their follower base and strategic objectives. For instance, top influencers may not need to compete for peak hours since they already have strong audience loyalty, whereas established influencers might benefit from streaming on weekends when viewership tends to be higher. Platforms can use these insights to refine algorithmic recommendations, optimize promotional timing, and provide influencers with better guidance on when to stream for maximum impact.

Second, this research challenges misconceptions about the role of top influencers and celebrities in the market. Some influencers may perceive these popular influencers as direct competitors, assuming that streaming simultaneously with them would reduce their viewership. However, our findings reveal that top influencers and celebrities generate positive spillover effects —expanding the overall audience sizes across the platform. Rather than avoiding competition, less prominent influencers may strategically position themselves to benefit from the market expansion effects driven by top influencers and celebrities. A clearer understanding of this dynamic could help influencers and platform managers refine competitive strategies and foster a more collaborative ecosystem.

Finally, our study demonstrates that, contrary to common belief, maintaining a consistent streaming schedule does not improve show viewership or sales. While scheduling consistency may foster audience loyalty and habitual engagement over the long term, these benefits may not be immediately reflected in the short-term show outcomes. Moreover, if a fixed schedule imposes additional costs or operational constraints that outweigh its long-term benefits, influencers should reconsider its necessity.

3.9.3. Limitations and Future Research Directions

While our study provides valuable insights into influencers' timing decisions in livestream shopping, its limitations present opportunities for future research. First, we focus on top influencers and established influencers, whose scheduling decisions significantly impact the market. However, the timing strategies of emerging influencers, who often operate under different constraints and competitive dynamics, remain an important avenue for further exploration. Second, while we reveal key discrepancies between timing decisions and show outcomes, the underlying mechanisms driving these discrepancies require deeper investigation. Future studies could explore behavioral, economic, or algorithmic factors that shape influencers' decision-making processes. Finally, as the first study to examine strategic timing decisions in livestream shopping, we hope our work lays the foundation for a broader research agenda in this emerging field. We encourage scholars to build on our findings and further investigate the complex interplay between timing, competition, and consumer engagement in digital commerce.

4. Influencer Marketing under Brand Evolution

4.1. Introduction

Online influencers amass large followings by sharing self-curated content on social media platforms. For example, Charlie D'Amelio, known for her dance videos, has reached 155.4 million followers on TikTok (Statista, 2024). Similarly, PewDiePie, famous for his gaming commentary on YouTube, has also attracted 20.9 million followers on Instagram. By cultivating a sense of companionship with their audiences, online influencers build trust that enhances the perceived authenticity and reliability of their content (Lou & Yuan, 2019). Consequently, brands are increasingly embracing influencer marketing‒a strategy in which brands collaborate with influencers to promote brands' products or services (Leung et al., 2022)[8].

The influencer marketing industry has experienced substantial growth globally, rising from US$1.7 billion in 2016 to US$21.1 billion in 2023, with projections suggesting a further 14% increase by the end of 2024 (Influencer Marketing Hub, 2024). In Canada, spending on influencer marketing is expected to reach US$656.6 million in 2025 and grow at an annual rate of 10.36% by 2029 (Statista, 2024). With this rapid expansion, established brands such as Coca-Cola, Starbucks, Amazon, and Walmart, as well as emerging ones such as Blue Apron, HelloFresh, Mejuri, and Allbirds, have incorporated influencer partnerships into their marketing strategies.

Brands strive to leverage influencers' popularity and their interactive engagement with consumers to enhance brand awareness and drive sales. Within these partnerships, influencers are dedicated to creating and sharing content for the brand, while the brand compensates influencers for their promotional efforts. Compensation plans may vary based on influencer popularity and

[8] Influencer marketing differs from celebrity endorsement, which lacks direct consumer engagement and involves limited control over content creation. In addition, unlike online influencers, celebrities have built their fame in a formal institutional setting, such as in sports, music, or film industry (Leung et al., 2022).

brand awareness, shaping influencers' motivation to promote the brand. An influencer's promotional efforts, along with brand awareness and influencer popularity, collectively determine the success of the collaboration.

Moreover, the outcomes of contemporary brand-influencer collaborations often drive the long-term evolution of both influencer popularity and brand awareness, adding further complexity to these partnerships. For instance, as a brand gains awareness through influencer collaborations, it may become less reliant on influencers and seek to reduce marketing expenditures on influencer compensation. Both brands and influencers aim to understand these dynamic interdependencies and optimize their strategies to sustain mutually beneficial partnerships. Specifically, brands seek to design optimal compensation plans that support continued growth and long-term collaboration effectiveness.

Despite the growing concerns about the dynamics of brand-influencer relationships, limited research has explored the impact of these collaborations on a brand's long-term growth. Therefore, we aim to answer the following research questions: How can a brand motivate an influencer as their relationship evolves? How do an influencer's promotional efforts change over time? Shall the brand opt for a long-term contract to drive sustained growth? If so, decide whether to collaborate with a big or multiple small influencers.

To answer these questions, we develop a game-theoretical model and explore its implications. Our analysis reveals several key insights. First, brands tend to overpay influencers, with emerging brands wasting less money than established ones when collaborating with the same influencer. Second, an influencer invests more in promotional efforts under a long-term contract, especially in the initial period. In addition, brands also secure greater profits under a long-term contract than a dynamic one. Finally, partnering with a single big influencer is more profitable than collaborating with multiple small influencers who collectively have an equivalent follower base.

Our findings contribute to the literature by shedding light on the dynamics of brand-influencer partnerships. This study advances the understanding of how brands can strategically nurture long-term relationships with influencers to foster sustainable growth. Additionally, we extend the theoretical foundation of influencer marketing by highlighting the importance of long-term brand growth through influencer collaborations. From a managerial perspective, our study offers actionable insights for both brands and influencers. It prompts brands to rethink their influencer marketing strategies, particularly when aiming for long-term success. When selecting influencers, brands must also carefully consider factors such as their current brand awareness and average prices to optimize their collaboration strategies.

4.2. Literature Review

Emerging analytical research in marketing and economics has explored various mechanisms within influencer marketing. For example, Kuksov and Liao (2019) analyze how influencers' recommendations affect consumers' inference on product quality and brands' product line design. Mitchell (2021) studies the dynamic relationship between an influencer and a follower, accounting for the influencer's trade-off between good advice and brand sponsorship. Similarly, Nistor and Selove (2024) build a dynamic model to examine how the followers' comments affect influencers' growth and brand sponsorships. Complementing this work, several analytical papers have explored influencer compensation mechanisms. Jain and Qian (2021) examine how digital platform compensates the content creator to incentivize the content creation, while Pei and Mayzlin (2021) explore a firm's decision to affiliate with influencers and compensate them based on the persuasiveness of influencers' reviews. Fainmesser and Galeotti (2021) examine influencers' trade-off between non-sponsored content and revenue. In their model, brands bid for influencers' endorsement and pay the influencer based on each post. While these papers enrich our understanding of the compensation plans, influencer-follower, and influencer-brand relationships, they have ignored the compensation plans in the evolving brand-influencer partnerships. This paper aims to extend the literature by developing a theoretical model that captures the evolving dynamics of brand-influencer collaborations over the long term.

Parallel to this analytical work, a growing body of empirical research on influencer marketing has identified several key factors that shape brand-influencer collaborations, including influencers' characteristics (Beichert et al., 2024; Leung et al., 2022 a; Valsesia et al., 2020; Wies et al., 2022), brand-influencer fit (Breves et al., 2019, Kim & Kim, 2021; Leung et al., 2022 b), influencer-product fit (Belanche et al., 2021), and content characteristics (Hughes et al., 2019; Pan et al., 2024; Tian et al., 2023). These studies demonstrate how such factors affect consumer engagement and product sales. However, while recent research advocates for leveraging brand-influencer collaborations to achieve long-term benefits (Wu et al., 2022; Cheng & Zhang, 2024), the literature primarily focused on short-term partnerships, overlooking the dynamics of influencer popularity, influencer promotional efforts, brand awareness and sales for sustained growth. This paper addresses this concern.

Our paper is also broadly related to the literature on salesforce compensation. One stream of research focuses on quota-based contracts, highlighting the factors such as salesmen's risk tolerance (Basu et al., 1985), bonus structure (Chung et al., 2013; Kim, 1997), and varying quotas (Raju & Srinivasan, 1996). Another stream examines salesmen's compensation plans that are tied to sales, arguing that salesmen optimize their benefits and the firm's profits simultaneously (Farley, 1964; Weinberg, 1975). Within this latter stream, scholars have explored variations of marginal cost (Davis & Farley, 1971; Farley & Weinberg, 1974) and price control (Weinberg, 1975). Darmen (1978) emphasizes the importance of considering the effects of salespeople's previous activities when designing compensation plans to maximize long-term profits. Building on this foundation, this paper extends the literature by enhancing the theoretical understanding of the compensation plans, considering the dynamics of influencer popularity, promotional efforts, brand awareness, and sales in influencer marketing.

4.3. Context

Influencer marketing has become an important strategy for brands to engage with consumers, as consumers are more likely to trust and engage with influencers (Statista, 2024). As a result, over 85% of the brands intend to dedicate a budget for influencer marketing, with 24.2% allocating more than 40% of their marketing spend (Influencer Marketing Hub, 2024). Typically, brands offer various incentives, including monetary compensation, to encourage influencers to promote their products or services. The effectiveness of these collaborations is evaluated based on sales outcomes. However, influencers' compensation and sales outcomes, along with influencers' popularity in the previous campaigns, may also affect these factors in future brand collaborations.

When selecting influencers, brands often consider influencers' follower count as an indicator of audience reach. Influencers with large numbers of followers can enhance brand visibility by reaching a wider audience (Dogtiev, 2023), while small influencers with relatively fewer followers may dedicate more time to engaging with their audience (Beichert et al., 2024). Brands are also encouraged to collaborate with prospective influencers who are new to the social media platforms, taking a forward-looking approach (Lanz et al., 2024). However, the success of such an approach depends on building a lasting relationship with the same influencers. Notably, in practice, the proportion of brands working with the same influencers over time has increased from 57% in 2022 to 63.2% in 2024 (Influencer Marketing Hub, 2024). This trend indicates a shift in cultivating a long-term brand-influencer partnership.

A brand may collaborate with an influencer through either a long-term contract or a dynamic, short-term one. Under a long-term contract, the influencer agrees on the compensation rate for multiple campaigns. However, in a dynamic contract, the brand could adjust the compensation rates for each campaign based on past performances. Once the contract is signed, the influencer then prepares content, posts the content on social media platforms, and engages with the audience. After the campaign, the brand evaluates and pays the influencer based on sales generated in the campaign. In our benchmark model, we first depict the long-term collaboration, assuming the influencer will collaborate with the brand under a long-term contract. In the model extension, we will then discuss the case where the brand collaborates with the influencer under a dynamic contract.

4.4. Benchmark Model

4.4.1. Model Setup

We consider a two-period model to capture the dynamics of the long-term collaboration between brand b and influencer i. The brand's existing level of brand awareness influences a proportion of consumers to purchase its products. This proportion, denoted as $\rho \in [0,1]$, represents the share of the potential market influenced by existing brand awareness. For simplicity, we normalize the market to 1.

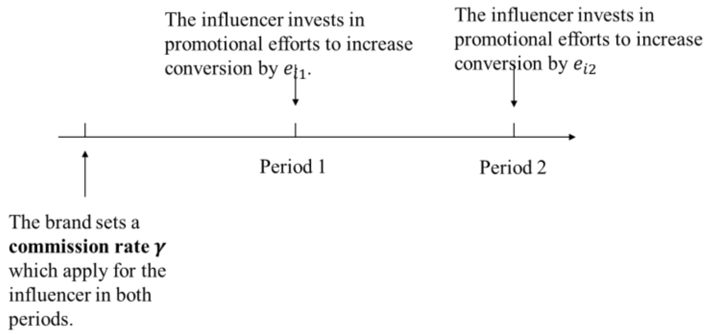
The influencer has a follower base of n within the potential market. In each period t (t = 1 or 2), the influencer invests in promotional efforts during the campaign that results in a conversion rate of e_t[9]. The influencer incurs a fixed cost, denoted as c_f , and an additional cost c for promotional efforts. All converted consumers purchase the brand's product at an average retail price of p.

Figure 4.1 depicts the timeline of the events under a long-term contract. The sequence unfolds as follows. At the beginning of period 1, the brand initiates collaboration with the influencer and sets the commission rate at γ. The influencer then decides the level of promotional efforts, resulting in a conversion rate at e_1 for period 1. After observing the results in period 1, the influencer adjusts the promotional efforts for period 2, resulting in a new conversion rate of e_2.

The total converted consumers in period 1 (i.e., first-period buyers) consists of two groups: those who purchase due to the existing brand awareness (ρ) and those converted among the influencer's followers ($e_1 n$). In period 2, the first-period buyers($\rho + e_1 n$) also generate word-of-mouth effects, influencing the non-converted consumers in the market at the rate of h. As a result, the conversion rate based on word-of-mouth effects is $h(\rho + e_1 n)$. Furthermore, converted consumers in period 1 continue to make purchases in period 2, contributing to additional sales quantity of $e_1 n$ for period 2.

Figure 4.1 Timeline of the Events Under a Long-term Contract

[9] Influencer's promotional efforts include, but not limited to, creating content, engaging with the audience, and/or promoting the products.



Now, we examine the objectives for the influencer and the brand in each period. In period 1, some of the influencer's followers make purchases due to the brand's existing awareness ρ, while others buy products because of the influencer's promotional efforts, such as product demonstration and real-time interactions with the audience, leading to a conversion rate among followers of e_1. Consequently, the total number of converted followers in the influencer's campaign is $(\rho + e_1)n$. Therefore, the influencer's profit function in period 1 is:

$$\pi_{i1} = \gamma(\rho + e_1)np - \left(c_f + ce_1^2\right) \tag{1}$$

Meanwhile, the brand's profit in period 1 consists of two parts: profit independent of influencer's collaboration (i.e., based on existing awareness), $\rho(1 - n)p$, and additional profit generated from the influencer's campaign, $(1 - \gamma)(\rho + e_1)np$. Therefore, the brand's function in period 1 is:

$$\pi_{b1} = \rho(1 - n)p + (1 - \gamma)(\rho + e_1)np \tag{2}$$

In period 2, some consumers may purchase the products due to brand awareness (ρ); First-period buyers exert word-of-mouth effects on non-converted consumers, leading to an additional conversion of $h(\rho + e_1 n)$. Moreover, first-period buyers will continue to purchase, leading to conversion of e_1 in period 2. Meanwhile, the influencer invests in promotional efforts that lead to a conversion rate of e_2 among followers. Thus, the influencer's profit function in period 2 is:

$$\pi_{i2} = \gamma(\rho + h(\rho + e_1 n) + e_1 + e_2)np - \left(c_f + c \cdot e_2^2\right) \tag{3}$$

The brand's total profit comprises profits outside of the influencer's channel and the profits from the influencer's channel:

$$\pi_{b2} = \underbrace{\big(\rho + h(\rho + e_{i1}n)\big)(1-n)p}_{Profits\ outside\ of\ the\ influencer's\ channel} + \underbrace{(1-\gamma)(\rho + h(\rho + e_1 n) + e_1 + e_2)np}_{profits\ from\ the\ influencer's\ channel} \quad (4)$$

Model notation is summarized in Table 4.1.

Table 4.1 Model Notation

Parameters	
i	Influencer *i*
b	Brand b
t	Period $t \in \{1,2\}$
h	Rate of word-of-mouth effects
p	Average price consumers pay
ρ	Brand awareness
n	The proportion of followers for influencer *i*
c	Influencer *i'* s marginal cost
c_f	Influencer *i*' s fixed cost
π_{it}	Influencer's profit in period *t*
π_{bt}	Brand's profit in period *t*
Decision Variables	
γ	Commission rate under a long-term contract
γ_t	Commission rate in period t under a dynamic contract
e_t	Conversion by influencer *i*'s effort in period *t*

4.5. Model Analysis

We use backward induction to analyze the sequential game between the brand and the influencer, as depicted in **Error! Reference source not found.**. First, we determine the i nfluencer's optimal conversion in period 2 given the commission rate γ. Based on the influencer's profit function given in Equation (3), we obtain the optimal efforts in period 2 that lead to a conversion rate at $e_2 = \frac{\gamma np}{2c}$. Intuitively, a high commission rate motivates the influencer to invest more in promotional efforts in period 2. In addition, the influencer with a higher number of followers is also motivated to invest more promotional efforts to increase the conversion rate. This is because the influencer with a higher number of followers expects more conversions than the influencer with fewer followers. Third, a high average price also motivates the influencer to invest in more promotional efforts, given the same cost of promotional efforts.

In period 1, influencer *i* decides the promotional efforts that lead to a conversion rate of e_1 to maximize the total profits over two periods. Solving the influencer's profit maximization problem, we obtain the following:

$$e_1 = \frac{\gamma np}{2c}(2 + hn) \tag{5}$$

Proposition 1: *Under a long-term contract, the influencer allocates greater promotional efforts to increase the conversion rate in period 1.*

Proposition 1 shows that the influencer invests more promotional efforts to boost conversions in the first period under a long-term contract. Increased conversion rates in period 1 amplify the word-of-mouth effects, which the influencer can then leverage in the future. Specifically, followers who made purchases in the first period are likely to influence others who have not yet made purchases. These non-converted consumers may participate in future campaigns where the influencer continues promoting the same brand. Since the influencer anticipates ongoing collaboration with the brand, their promotional efforts in period 1 continue to sustain engagement and sales in the subsequent campaign. Thus, to maximize the benefits from word-of-mouth effects generated by first-period buyers, the influencer is motivated to maximize conversions in period 1 under a long-term contract.

From the brand's perspective, anticipating the influencer's decisions, the brand sets a commission rate γ, to maximize its total profit over both periods. By solving the brand's optimization problem, we obtain:

$$\gamma = \frac{1}{2}\left(1 + \frac{h(2+hn)(1-n)}{1+(2+hn)^2} - \frac{\rho}{p}\cdot\frac{2c}{n}\cdot\left(\frac{2+h}{1+(2+hn)^2}\right)\right) \tag{6}$$

Proposition 2: *Under a long-term contract, the brand reduces excess commission payments to the influencer based on the existing level of brand awareness.*

Proposition 2 suggests that the brand raises the commission rate to motivate the influencer to invest more in promotional efforts during the initial period of a long-term contract. The influencer's efforts increase conversions, enhancing future brand awareness. However, as brand awareness grows, the brand may reduce the commission rate to avoid "unnecessary expenses" since some consumers may purchase products from the influencer's campaign based on existing brand awareness, resulting in the brand overpaying the influencer.

Consequently, both the established brand and emerging brand adjust the commission rates accordingly. When collaborating with the same influencer, an established brand with higher brand awareness may reduce the commission more significantly, as more conversions from the influencer's campaign may be driven by the existing brand awareness given the same average price. In contrast, emerging brands with lower brand awareness tend to reduce the commission less, aiming to incentivize the influencer and foster a long-term collaboration.

Now, we look at the brand's total profits, which is the sum of its profits in period 1 and period 2:

$$\underset{\max \gamma}{\pi_b} = \underbrace{\rho p + (1-\gamma)e_1 np}_{profits\ in\ Period\ 1} + \underbrace{\big(\rho + h(\rho + e_1 n)\big)p + (1-\gamma)(e_1 + e_2)np}_{profits\ in\ Period\ 2} \tag{7}$$

We obtain the brand's total profits by substituting the influencer's optimal conversions and the brand's commission rate into the profit function. By comparing the total profits for the established and emerging brand under the long-term contract, we derive the following insights (See Appendix C for simulation results)

Proposition 3: *Under a long-term contract for an established brand:*

a. *When the average price is high, the brand gains more profits by collaborating with a small or big influencer rather than one with a medium-sized following.*

b. *When the average price is low, the brand's profits decrease with the increase in the number of followers the influencer has.*

Interestingly, when the average price is high, the established brand gains more profit by partnering with either a small or big influencer, but not the influencer with a medium-sized following. When the average price is high, the brand is willing to pay a higher commission to incentivize the influencer with a large following count to leverage their fame. The brand may also want to leverage the niche market with smaller influencers, even though the brand may pay excess commission due to their brand awareness. However, when the average price is low, it is not profitable to partner with the big influencer, as sales generated may not outweigh the "unnecessary expense" the brand paid.

Proposition 4: *Under a long-term contract for an emerging brand,*

a. When the average price is high, the brand's profits increase with the influencer's follower count.

b. When the average price is low, the brand gains more profits by collaborating with a small or big influencer rather than one with a medium-sized following

Proposition 4 reveals that the benefit of an emerging brand's collaboration with an influencer depends on the average price. Unlike an established brand, an emerging brand has less brand awareness. The brand relies more on the influencer to enhance its visibility, reducing the chances for the influencer to free ride. Therefore, when the average price is high, the emerging brand is willing to pay a higher commission to incentivize an influencer as their number of followers increases.

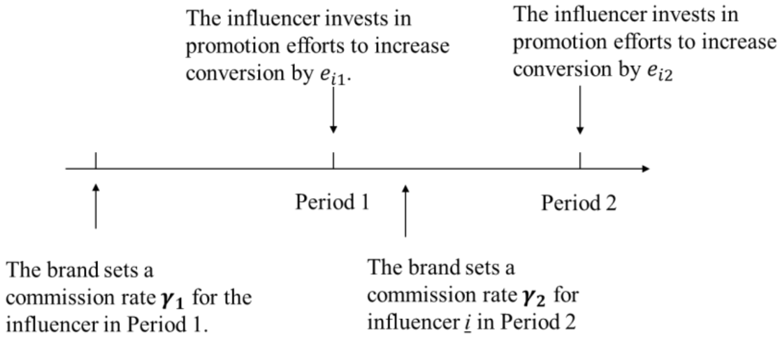
Counterintuitively, collaborating with an influencer with either a small or big influencer when the average price is low. This is because the brand may benefit from the niche market smaller influencer reaches. In addition, an influencer with a higher follower count may have greater word-of-mouth effects among their followers, leading to higher sales and reduced unnecessary expenses for the brand. Therefore, the brand benefits more from either working with a small influencer or a big influencer.

4.6. Model Extension: Collaboration Under a Dynamic Contract

As discussed in the main model, when a brand signs a long-term contract with an influencer, the brand may incur unnecessary expenses based on the brand's existing awareness. This raises the question of whether such "wasted" expenses could be mitigated through a dynamic contract, where the brand adjusts commission rates at different periods.

To address this, we extend the model to consider a dynamic contract with the influencer; That is, the brand first sets, γ_1 and the influencer decides on the promotional efforts that lead to a conversion of e_1. Observing the results in period 1, the brand then sets γ_2 in the second period. Given γ_2, then the influencer decides on promotional efforts that lead to a conversion rate of e_2 in period 2. The sequence of the events is shown in Figure 4.2.

Figure 4.2 Timeline of the Events Under a Dynamic Contract



Because the influencer now decides how much effort to invest in after each period, the objective functions for the influencer are as follows for each period respectively:

$$\pi_{i1} = \gamma_1(\rho + e_1)np - \left(c_f + c \cdot e_1^2\right) \tag{8}$$

$$\pi_{i2} = \gamma_2(\rho + h(\rho + e_1 n) + e_1 + e_2)np - \left(c_f + c \cdot e_2^2\right) \tag{9}$$

For the brand, the objective is to maximize the profit in each different period. Therefore, we have the following objective functions for the brand in each period respectively:

$\pi_{b1} = \rho(1 - n_i)p + (1 - \gamma_1)(\rho + e_1)np$;

$\pi_{b2} = \big(\rho + h(\rho + e_1 n)\big)(1 - n)p + (1 - \gamma_2)(\rho + h(\rho + e_1 n) + e_1 + e_2)np$

Using backward induction, we obtain the following results for the influencer:

$$e_1 = \frac{1}{2}\left(\left(\frac{\frac{1}{2}(1+hn)+2\gamma_1}{1+\frac{3}{4}(1+hn)^2}\right) \cdot \frac{np}{2c} - \rho \cdot \frac{\frac{3}{2}(1+hn)(1+h)}{1+\frac{3}{4}(1+hn)^2}\right) \tag{10}$$

$$e_2 = \frac{\gamma_2 np}{2c} \tag{11}$$

This suggests that under a dynamic contract, the influencer's promotional efforts in each period depend on the commission rate for that period. In period 1, the influencer adjusts the level of effort based on existing brand awareness, investing more promotional effort for an emerging brand than an established one.

For the brand, we have the optimal commission rate for each period as follows:

$$\gamma_1 = \frac{1}{2}\left(\alpha - \frac{\rho}{\frac{np}{2c}} \cdot \beta\right) \tag{12}$$

Where $\alpha = \frac{\left(\frac{5}{2}+2h\left(1-\frac{3}{4}n\right)\right)\left(2+\frac{3}{2}(1+hn)^2\right)+\frac{5}{4}(1+hn)^3}{4+2(1+hn)^2}$, and $\beta = \frac{\left(\frac{5}{2}+2h\left(1-\frac{3}{4}n\right)\right)\left(2+\frac{3}{2}(1+hn)^2\right)+\frac{5}{4}(1+hn)^3}{4+2(1+hn)^2}$

$$\gamma_2 = \frac{1}{2} - \frac{1+h}{2} \cdot \frac{\rho}{\frac{np}{2c}} - \frac{1+hn_i}{2} \cdot \frac{e_1}{\frac{np}{2c}} \tag{13}$$

Note that under a dynamic contract, the brand reduces the commission rate in the latter period based on the influencer's promotional efforts in the first period. This adjustment is made because the brand recognizes the word-of-mouth effects from the converted consumers and understands that they may overpay the influencer without the downward adjustment.

By comparing the profits for established and emerging brands under both contracts, we obtain the following findings:

Proposition 5: *Comparing the profits under a long-term contract and a dynamic contract, the brand's profit is always higher under a long-term contract.*

Counterintuitively, under a dynamic contract, a brand incurs fewer unnecessary expenses paid to the influencer since the brand can adjust commission rates in subsequent collaborations. However, brands tend to gain more profits when they sign a long-term contract with the influencer. Such a long-term contract enables the brand to build trust with the influencer, encouraging the influencer to invest more in promotional efforts, especially in the first period. Therefore, despite the flexibility of adjusting commission rates periodically under a dynamic contract, brands generally benefit more from long-term contracts due to the enhanced commitment and efforts from the influencer.

4.7. Model Extension: Collaborating with Multiple Influencers

In the main model, we analyze a setting with one brand and one influencer to demonstrate how brands collaborate with influencers for long-term growth. Many brands also wonder if they should collaborate with one big influencer or multiple small influencers with the same level of following base. Therefore, we extend the model to explore the scenario where the brand collaborates with multiple influencers to reach a wider audience. To understand how a brand achieves long-term growth through these collaborations, we consider two key model extensions: a) whether the brand should collaborate with multiple smaller influencers or one big influencer, and b) the impact of influencers' willingness to collaborate with the brand at different points in time.

4.7.1. Collaboration with Multiple Small Influencers

We begin by setting up the extended model. The brand collaborates with multiple influencers (denoted by $i = 1, 2 \ldots . m$) in each period. Each influencer has a proportion n_i of followers among the potential consumers. A total of *m* homogeneous influencers collaborate with the brand in both periods. The sequence of the events is as follows: at the beginning of period 1, the brand sets the commission. Then, influencer *i* decides how much effort to invest to lead to a conversion rate e_{i1} and e_{i2} in period 1 and period 2, respectively.

We assume that all the influencers are homogenous with a proportion of *n* followers. Each influencer aims to maximize her own profit in each period. Therefore, the profit function for influencer *i* in period 1 is:

$$\pi_{i1} = \gamma(\rho + e_{i1})np - \left(c_{if} + c_i \cdot e_{i1}^2\right) \tag{14}$$

In period 2, the proportion of consumers who bought the products in period 1, $(\rho + mne_{i1})$, will influence the rest of the consumers in the market, and generate word-of-mouth effects at the rate of h. Thus, the profit function is :

$$\max_{e_{i2}} \pi_{i2} = \gamma(\rho + h(\rho + mne_{i1}) + e_{i1} + e_{i2})n_i p - \left(c_{if} + c_i \cdot e_{i2}^2\right) \tag{15}$$

Since the brand sets the commission rate at the beginning of period 1 under a long-term contract, the profit function for the brand is :

$$\max_{\gamma} \pi_b = \pi_{b1} + \pi_{b2} \tag{16}$$

Where $\pi_{b1} = \rho(1 - mn)p + (1 - \gamma)(\rho + e_{i1})mnp$,

$$\pi_{b2} = \left(\rho + h(\rho + mne_{i1})\right)(1 - mn)p + (1 - \gamma)(\rho + h(\rho + mne_{i1}) + e_{i1} + e_{i2})mnp$$

We use backward induction to derive the following results for the influencer *i*'s effort in each period:

$$e_{i1} = \frac{\gamma np}{2c_i}(2 + hmn) \tag{17}$$

$$e_{i2} = \frac{\gamma np}{2c_i} \tag{18}$$

We observe that influencer *i* invests more effort in period 1. With more influencers, each influencer converts a proportion of consumers into converted consumers. As more consumers make purchases from *m* influencers in period 1, the resulting word-of-mouth effects create benefits for all influencers in period 2. This positive spillover effect encourages influencer *i* to invest more effort in period 1.

Substitute $e_{i2} = \frac{\gamma np}{2c_i}$ and $e_{i1} = \frac{\gamma np}{2c_i}(2 + hmn)$ into the above equation and take the first order condition with respect to γ, we obtain:

$$\gamma = \frac{1}{2}\left(1 + \frac{h(2+hmn)(1-mn)}{1+(2+hmn)^2} - \frac{\rho}{\frac{np}{2c_i}} \cdot \left(\frac{(2+h)}{1+(2+hmn)^2}\right)\right) \tag{19}$$

4.7.2. One Big Influencer vs. Multiple Small Influencers

Suppose the brand collaborates with one big influencer, whose proportion of followers, *Mn,* equals the combined proportions of followers of all smaller influencers. The brand sets the commission rate at γ_M. Now, the profit function for influencer *i* in period 1 is :

$$\pi_{i1} = \gamma_M(\rho + e_{i1})Mnp - \left(c_{if} + c_i \cdot e_{i1}^2\right) \tag{20}$$

In Period 2, the word-of-mouth effects from converted consumers in period 1 affect the rest of the consumers in the market. Thus, the profit function is :

$$\max_{e_{i2}} \pi_{i2} = \gamma_M(\rho + h(\rho + Mne_{i1}) + e_{i1} + e_{i2})Mnp - \left(c_{if} + c_i \cdot e_{i2}^2\right) \tag{21}$$

Under a static contract, the brand sets the commission rate at the beginning of period 1. Hence, the brand's profit function is :

$$\max_{\gamma_M} \pi_b = \pi_{b1} + \pi_{b2} \tag{22}$$

Where $\pi_{b1} = [\rho(1 - Mn)p + (1 - \gamma_M)(\rho + e_{i1})Mnp]$,

$$\pi_{b2} = \Big(\big(\rho + h(\rho + Mne_{i1})\big)(1 - Mn)p + (1 - \gamma_M)(\rho + h(\rho + Mne_{i1}) + e_{i1} + e_{i2})Mnp\Big)$$

We use backward induction to derive the following results:

$$e_{i1} = \frac{\gamma_M Mnp}{2c_i}(2 + hMn) \tag{23}$$

$$e_{i2} = \frac{\gamma_M Mnp}{2c_i} \tag{24}$$

This result suggests that the big influencer invests even more effort in period 1, benefiting not only the strong word-of-mouth effects among the consumers but also receiving higher compensation for her efforts.

Substitute the above results into the brand's profit function and take the first order condition with respect to γ_M, we obtain:

$$\gamma_M = \frac{1}{2}\left(1 + \frac{h(2+hMn)(1-Mn)}{1+(2+hMn)^2} - \frac{\rho}{\frac{Mnp}{2c_i}} \cdot \left(\frac{2+h}{1+(2+hMn)^2}\right)\right) \tag{25}$$

Comparing the results when the brand collaborates with multiple small influencers or one big influencer, we find that the brand benefits more from collaborating with one big influencer than with multiple influencers, even when the total follower count is equivalent. One potential explanation is that the big influencer may exert more effort to convert their audience into converted consumers, as their higher commission rates provide a strong incentive.

4.7.3. Other Model Extensions

When influencers can decide when to collaborate with the brand, especially for new products, they may fall into two groups: early adopters who collaborate with the brand to promote the new products and late adopters who observe first and delay their collaboration. Influencers who joined later benefit from those who promoted the brand earlier, as they understand more about market reaction to the new products. However, if early adopters have signed a long-term contract, their compensation may not account for this additional influence they provide for later adopters. Therefore, brands need to determine the optimal compensation design to incentivize long-term collaboration for new products accounting for this possibility.

In addition, in our current models, we assume the number of followers remains constant. However, an influencer's follower count may increase or decrease after collaborating with the brand, depending on the performance of the campaign. Another potential model extension would explore how changes in influencers' popularity impact long-term brand-influencer collaboration.

4.8. Conclusion

Influencer marketing has become a widely adopted marketing strategy for brands. However, current practices and literature mainly focus on short-term brand-influencer collaborations. In this paper, we develop an analytical model to investigate how brands collaborate with influencers to achieve long-term growth. Our analysis shows that brands pay unnecessary money to influencers, and the extent of these overpayments depends on brand awareness and average prices. In addition, brand awareness and prices are important factors to consider when choosing influencers with varying levels of popularity. Additionally, we explain why a long-term contract is more beneficial than a dynamic one. Furthermore, our model extension demonstrates that partnering with a single big influencer is more profitable than collaborating with multiple small influencers who collectively have an equivalent follower base. Our findings advance the understanding of brand-influencer collaboration and offer practical guidance for brand managers to rethink their influencer strategies for long-term growth.

5. Conclusion

This dissertation examines the externalities related to marketing strategies and addresses gaps in understanding their impacts across contexts in the digital marketing landscape. Using a combination of analytical models, fixed effects model, and logit model for panel data, it explores how externalities shape strategic marketing decisions and business outcomes.

Chapter 1 synthesizes relevant literature on how common externalities influence marketing strategies from three perspectives: marketplaces, firms, and consumers. It also extends the definition of externality to include self-imposed spillovers that are not fully internalized by the same agent. Based on this definition, the subsequent chapters examine the impact of various externalities on marketing strategies, such as platform economy, livestream shopping, and influencer marketing.

In the platform economy, cross-platform network effects arise when multi-homing users connect two platforms, resulting in externalities between two marketplaces. Chapter 2 depicts the mechanism of cross-platform network externalities and derives the findings on how cross-platform network externalities reshape platform pricing strategies. To attract more users to the platform, platforms could leverage the positive cross-platform network externalities by strategically lowering the prices to the users on the side with multi-homers and adjusting the price for the single-homing users on the other side to different extent based on the multi-homers' synergies.

On the livestream shopping platform, influencers strategically schedule their livestream shows to engage with their audience and generate sales. Chapter 3 empirically examines two types of externalities in this emerging business model. The first is scheduling consistency, a form of temporal externality that arises from an influencer's own repeated scheduling behavior. The second is spillover effects, which reflect peer-based externalities generated by other influencers, particularly high-profile ones such as top influencers and celebrities. My study reveals the discrepancies between influencers' perceptions of these externalities and their actual effects. Influencers tend to maintain a certain level of scheduling consistency, anticipating a positive impact. However, the empirical results indicate that consistent scheduling has no significant impact on show outcomes. In addition, influencers deliberately avoid scheduling their shows concurrently with top influencers or celebrities due to concerns about negative spillover effects. Nevertheless, our findings indicate that top influencers and celebrities exert a positive impact on focal influencers' show outcomes. These insights highlight the need for influencers to re-evaluate their timing strategies in light of the nuanced impacts of both intra- and inter-firm externalities in livestream shopping.

As influencer marketing gains more traction, externalities arise between brands and influencers (collaborating firms), as well as among consumers through word-of-mouth effects. Chapter 4 studies how these two types of externalities affect brand-influencer collaboration. An influencer's popularity enhances brand awareness, while the evolution of the brand may, in turn, affect influencers' promotional efforts. In addition, externalities exist among an influencer's audience, as one audience's purchase can influence the purchasing decisions of others. The preliminary findings from the analytical models suggest that brands could adjust the compensation plan in the presence of these externalities, and a long-term contract could be more profitable than a dynamic one.

In an era marked by rapid technological advancement and an increasingly connected and dynamic marketing environment, externalities are poised to play an ever more influential role in shaping marketing strategies. This dissertation examines a range of externalities—spanning across markets, between competing and collaborating firms, within firms, and among consumers—and proposes a framework for understanding how these interdependencies influence strategic decisions and marketing outcomes. By shedding light on the complex ways externalities manifest across different contexts, this work aims to enrich the broader discourse on strategic marketing and inspire further scholarly inquiry into the multifaceted role of externalities in marketing.

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7. Appendices

Appendix A Supplementary Materials for Chapter 2

A.1. Proof of Proposition 1

A.1.(i). *Both $\mathcal{M}_A$ and $\mathcal{M}_B$ are greater than 1, or, cross-platform network effects are always multiplying;*

$\mathcal{M}_A = \frac{1-T^{aA}}{1-T^{aA}-T^{mA}} = 1 + \frac{T^{mA}}{1-(T^{aA}+T^{mA})}$. According to definition 1, $T^{mA} = \frac{\partial u_i^m}{\partial n_j^A} \cdot \frac{\partial n_i^m}{\partial u_i^m} \cdot \frac{\partial u_j^A}{\partial n_i^m} \cdot \frac{\partial n_j^A}{\partial u_j^A} = \left(1 + \delta\alpha_i^B n_j^B\right)\alpha_i^A\alpha_j^A\phi'_{im}\phi'_{jA} \geq 1$. As condition 1 indicates, $1 + \delta\alpha_i^B n_j^B \geq 0$By condition 2 , $0 < T^{aA} + T^{mA} < 1$. Then $\frac{1}{1-(T^{aA}+T^{mA})}$ is always greater than one.; then we have $\mathcal{M}_A = 1 + \frac{T^{mA}}{1-(T^{aA}+T^{mA})} > 1$. Similarly, we get $\mathcal{M}_B > 1$.

A.1. (ii) $\frac{\partial \mathcal{M}_A}{\partial \delta} > 0$ *and* $\frac{\partial \mathcal{M}_B}{\partial \delta} > 0$*, or cross-platform multipliers are bigger when multi-homing users gain positive synergies from using the two platforms than when they face negative synergies.*

By definition 1, $T^{mA} = \left(1 + \delta\alpha_i^B n_j^B\right)\alpha_i^A\alpha_j^A\phi'_{im}\phi'_{jA}$and $T^{aA} = \alpha_i^A\alpha_j^A\phi'_{ia}\phi'_{jA}$

. We can rewrite $\mathcal{M}_A$ as $1 + \frac{\left(1+\delta\alpha_i^B n_j^B\right)\alpha_i^A\alpha_j^A\phi'_{im}\phi'_{jA}}{1-\left(\alpha_i^A\alpha_j^A\phi'_{ia}\phi'_{jA}+\left(1+\delta\alpha_i^B n_j^B\right)\alpha_i^A\alpha_j^A\phi'_{im}\phi'_{jA}\right)}$. Take derivative with respect to δ, $\frac{\partial \mathcal{M}_A}{\partial \delta} = \frac{1-T^{aA}}{\left(1-T^{aA}-T^{mA}\right)^2}$. By Condition 2, we get $1 - T^{aA} > 0$. Therefore, $\frac{\partial \mathcal{M}_A}{\partial \delta} > 0$. Similarly, we get $\frac{\partial \mathcal{M}_B}{\partial \delta} > 0$.

A. 1(iii) $\frac{\partial \mathcal{M}_A}{\partial T^{aA}} > 0$ *and* $\frac{\partial \mathcal{M}_B}{\partial T^{bB}} > 0$*, or, the cross-platform multiplier through a platform is positively correlated to the marginal impact of the feedback loop within the platform.*

Since $\mathcal{M}_A = 1 + \frac{T^{mA}}{1-(T^{aA}+T^{mA})}$, $\frac{\partial \mathcal{M}_A}{\partial T^{aA}} = \frac{T^{mA}}{\left(1-(T^{aA}+T^{mA})\right)^2}$. Because T^{mA}>0 and $0 < T^{aA} + T^{mA} < 1$, $\frac{\partial \mathcal{M}_A}{\partial T^{aA}} = \frac{T^{mA}}{\left(1-(T^{aA}+T^{mA})\right)^2} > 0$.

A.2. Proof of Proposition 2

By Lemma 3, the equilibrium price on side *i* of platform A is $p_i^A = f_i^A - \alpha_j^A n_j^A + \frac{n_i^a+n_i^m}{\phi'_{ia}+\phi'_{im}\cdot\mathcal{M}_B}$.

Because $\mathcal{M}_B > 1$, $\frac{n_i^a+n_i^m}{\phi'_{ia}+\phi'_{im}\cdot\mathcal{M}_B} > \frac{n_i^a+n_i^m}{\phi'_{ia}+\phi'_{im}} \cong \frac{n_i}{\phi'_i}$. p_i^A is less than the price compared with the price when two platforms are not interconnected by the multi-homers. Same logic applies to equilibrium price on side *i* of platform B.

A.3. Proof of Proposition 3

By lemma 3, the equilibrium price on side *i* of platform A is $p_i^A = f_i^A - \alpha_j^A n_j^A + \frac{n_i^a+n_i^m}{\phi'_{ia}+\phi'_{im}\cdot\mathcal{M}_B}$, where $\mathcal{M}_B > 1$. $\frac{n_i^a+n_i^m}{\phi'_{ia}+\phi'_{im}\cdot\mathcal{M}_B}$is smaller when users gain positive synergies (i.e., $\delta > 0$) than the case where users gain negative synergies (i.e., $\delta < 0$). Hence p_i^A is less when users gain positive synergies.

A.4. Proof of Proposition 4

Armstrong (2006) show that the equilibrium price on side j of platform A is: $p_j = f_j - \alpha_i n_i + \frac{n_j}{\phi_j'}$ when two platforms are not interconnected by the multi-homers. By lemma 4, when two platforms are interconnected by multi-homers, the equilibrium price on side j of platform A is : $p_j^A = f_j^A - \alpha_i^A n_i^A \cdot \frac{\phi_{ia}'+\phi_{im}'\mathcal{M}_B \cdot \left(1+\delta\alpha_i^B n_j^B\right)}{\phi_{ia}'+\phi_{im}'\mathcal{M}_B} + \frac{n_j^A}{\phi_{jA}'}$, where the external benefits, $\alpha_i^A n_i^A$, are adjusted by $\frac{\phi_{ia}'+\phi_{im}'\mathcal{M}_B \cdot \left(1+\delta\alpha_i^B n_j^B\right)}{\phi_{ia}'+\phi_{im}'\mathcal{M}_B}$. By Condition 1 and Proposition 1(i), $\left(1+\delta\alpha_i^B n_j^B\right) \geq 0$ *and* $\mathcal{M}_B > 1$ respectively , $\frac{\phi_{ia}'+\phi_{im}'\mathcal{M}_B \cdot \left(1+\delta\alpha_i^B n_j^B\right)}{\phi_{ia}'+\phi_{im}'\mathcal{M}_B}$ is greater than 0. Therefore, $-\alpha_i^A n_i^A \cdot \frac{\phi_{ia}'+\phi_{im}'\mathcal{M}_B \cdot \left(1+\delta\alpha_i^B n_j^B\right)}{\phi_{ia}'+\phi_{im}'\mathcal{M}_B}$ is smaller compared with $-\alpha_i n_i$, indicating that equilibrium price is lower on side j of platform A when two platforms are interconnected. If multi-homing users gain positive synergies $\delta > 0$, *then* $\left(1+\delta\alpha_i^B n_j^B\right) > 1$; On the other hand, if multi-homing users gain negative synergies, then $\left(1+\delta\alpha_i^B n_j^B\right) < 1$. Therefore, the external benefits $\alpha_i^A n_i^A$ are adjusted downward more in former case than in the latter case.

A.5. Proof of Proposition 5

By Lemma 5, when two platforms are independently owned and can differentiate multi-homers from single-homing users equilibrium *i*-side pricing by platform A is $p_i^A = f_i^A - \alpha_j^A n_j^A + \frac{n_i^a}{\phi_i^{a\prime}}$ for single-homing users, and $p_i^{Am} = f_i^A - \alpha_j^A n_j^A + \frac{n_i^m}{\phi_{im}'\mathcal{M}_B}$ for multi-homing users, For single-homing users on *i*-side of Platform A , the price is similar to pricing for *i*-side with only single-homing users. Meanwhile, platform A charges multi-homers $p_i^{Am} = f_i^A - \alpha_j^A n_j^A + \frac{n_i^m}{\phi_{im}'\mathcal{M}_B}$.

When multi-homers gain positive synergies, $\frac{n_i^m}{\phi_{im}'\mathcal{M}_B}$ is even lower than the case where multi-homers gain negative synergies.

A.5. Proof of Proposition 6

By lemma 6, when two platforms are independently owned and differentiate multi-homing users from the single-homing users on *Side i*, the equilibrium *j*-side pricing strategy by platform A is : $p_j^A = f_j^A - \alpha_i^A n_i^a - \alpha_i^A n_i^m\left(1+\delta\alpha_i^B n_j^B\right) + \frac{n_j^A}{\phi'_{jA}}$. If multi-homing users receive positive synergies (i.e., $\delta > 0$), then the external benefit $\alpha_i^A n_i^m$ is adjusted upward by $\left(1+\delta\alpha_i^B n_j^B\right)$, where $\left(1+\delta\alpha_i^B n_j^B\right)$>1; If multi-homing users receive negative synergies (i.e., $\delta < 0$), then the external benefit $\alpha_i^A n_i^m$ is adjusted upward by $\left(1+\delta\alpha_i^B n_j^B\right)$, where $0 \leq \left(1+\delta\alpha_i^B n_j^B\right)$<1. Therefore, Platform A offers more discounts to *j*-side users when multi-homing users gain positive synergies than negative synergies.

A.5. Proof of Proposition 7

Proposition is intuitive from Lemma 7.

A.6. Calculation of Equilibrium Prices in Section 5.

a) partial derivatives with respect to p_i^A

$$x = \frac{\partial n_i^a}{\partial p_i^A} = \phi'_{ia}\left(\alpha_i^A\left(\frac{\partial n_j^A}{\partial p_i^A}\right) - 1\right)$$

$$y = \frac{\partial n_i^m}{\partial p_i^A} = \phi'_{im}\left[\alpha_i^A\left(\frac{\partial n_j^A}{\partial p_i^A}\right) - 1 + \alpha_i^B\left(\frac{\partial n_j^B}{\partial p_i^A}\right) + \delta\alpha_i^A\left(\frac{\partial n_j^A}{\partial p_i^A}\right)\alpha_i^B n_j^B + \delta\alpha_i^A n_j^A \alpha_i^B\left(\frac{\partial n_j^B}{\partial p_i^A}\right)\right]$$

$$z = \frac{\partial n_j^A}{\partial p_i^A} = \phi'_{jA}\left[\alpha_j^A\left(\frac{\partial n_i^a}{\partial p_i^A} + \frac{\partial n_i^m}{\partial p_i^A}\right)\right]$$

$$s = \frac{\partial n_i^b}{\partial p_i^A} = \phi'_{ib}\cdot\alpha_i^B\left(\frac{\partial n_j^B}{\partial p_i^A}\right)$$

$$t = \frac{\partial n_j^B}{\partial p_i^A} = \phi'_{jB}\cdot\alpha_j^B\left(\frac{\partial n_i^b}{\partial p_i^A} + \frac{\partial n_i^m}{\partial p_i^A}\right)$$

b) partial derivatives with respect to p_j^A

$$g = \frac{\partial n_i^a}{\partial p_j^A} = \phi_{ia}' \cdot \alpha_i^A \left(\frac{\partial n_j^A}{\partial p_j^A}\right)$$

$$q = \frac{\partial n_i^m}{\partial p_j^A} = \phi_{im}' \left[\alpha_i^A \left(\frac{\partial n_j^A}{\partial p_j^A}\right) + \alpha_i^B \left(\frac{\partial n_j^B}{\partial p_j^A}\right) + \delta\alpha_i^A \left(\frac{\partial n_j^A}{\partial p_j^A}\right) \alpha_i^B n_j^B + \delta\alpha_i^A n_j^A \alpha_i^B \left(\frac{\partial n_j^B}{\partial p_j^A}\right)\right]$$

$$h = \frac{\partial n_j^A}{\partial p_j^A} = \phi_{jA}' [\alpha_j^A \left(\frac{\partial n_i^a}{\partial p_j^A} + \frac{\partial n_i^m}{\partial p_j^A}\right) - 1]$$

$$v = \frac{\partial n_i^b}{\partial p_j^A} = \phi_{ib}' \cdot \alpha_i^B \left(\frac{\partial n_j^B}{\partial p_j^A}\right)$$

$$w = \frac{\partial n_j^B}{\partial p_j^A} = \phi_{jB}' \cdot \alpha_j^B \left(\frac{\partial n_i^b}{\partial p_j^A} + \frac{\partial n_i^m}{\partial p_j^A}\right)$$

c) solve for solutions for partial derivatives (Details in online Web Appendix)

d) First order condition with respect to p_i^A and p_j^A:

$$\frac{\partial n_i^a}{\partial p_i^A}\left(p_i^A - f_i^A\right) + n_i^a + \frac{\partial n_i^m}{\partial p_i^A}\left(p_i^A - f_i^A\right) + n_i^m + \frac{\partial n_j^A}{\partial p_i^A}\left(p_j^A - f_j^A\right) = 0$$

$$\frac{\partial n_i^a}{\partial p_j^A}\left(p_i^A - f_i^A\right) + \frac{\partial n_i^m}{\partial p_j^A}\left(p_i^A - f_i^A\right) + n_i^m + \frac{\partial n_j^A}{\partial p_j^A}\left(p_j^A - f_j^A\right) + n_j^A = 0$$

Solve for x, y, z, s, t, g, q, h, v, w and substitute into F.O.C. We can derive:

$$p_i^A = f_i^A - \alpha_j^A n_j^A + \frac{(n_i^a + n_i^m)}{(\phi_{ia}' + \phi_{im}' \cdot \mathcal{M}_B)}$$

$$p_j^A = f_j^A + \frac{n_j^A}{\phi_{jA}'} - \alpha_i^A (n_i^a + n_i^m) \cdot \frac{\left(\phi_{ia}' + \phi_{im}' \cdot \mathcal{M}_B \cdot \left(1 + \delta\alpha_i^B n_j^B\right)\right)}{(\phi_{ia}' + \phi_{im}' \cdot \mathcal{M}_B)}$$

Where $\mathcal{M}_B = 1 + \frac{T^{mB}}{1-\left(T^{bB}+T^{mB}\right)}$; Similarly, we can derive p_i^B and p_j^B.

Appendix B Supplementary Materials for Chapter 3

B.1. Measurements of Variables

***Spillover*:** To measure spillover effects, we count the number of top influencers and celebrities whose shows overlap with the focal influencer's show. This requires comparing the start-time and end-time of all shows streamed on the same date as each of the focal influencer's shows. If a top influencer or celebrity's show overlaps with the focal influencer's show, they are included in the spillover count.

For example, if the focal influencer streams the show from 8:30 P.M. to 11 P.M. on September 8. On the same date, one top influencer streams the show from 7:15 P.M. to 11:15 P.M., and another top influencer streams from 9 P.M. to 11:30 P.M. Both shows overlap with the focal influencer's show. In this case, the spillover equals 2 for the focal influencer's show. This same logic applies if the focal influencer streams multiple shows on the same date.

***DayConsistency*:** We measure day consistency by comparing the day of the week on which each influencer streams a show with the prior week. If the focal influencer streams a show on the same day as the previous week, we assign a value of 1 for day consistency. For example, if an influencer streams a show on Monday, September 6 (i.e., Week 1 in the data period) and again on Monday, September 13 (i.e., Week 2), we assign a value of 1 for day consistency for the show streamed on Monday, September 13. For subsequent weeks, we continue this comparison with the preceding week to determine day consistency for each observation (e.g., shows in Week 3 are compared with those streamed by the same influencer in Week 2, and so on).

***TimeConsistency*:** As described in the "**Market context and preliminary evidence on timing in livestream shopping**" section of the main manuscript, we divided each day into four time intervals: *Night* (12:00 A.M. − 5:59 A.M.), *Morning* (6:00 A.M −11:59 A.M), *Afternoon*

(12:00 P.M. −5:59 P.M.), and *Evening* (6:00 P.M. −11:59 P.M.). We assigned each show to a time interval in which the majority of its duration occurred.

We measure time consistency by comparing the time interval of each influencer's show with their most recent prior show date. If a show is streamed during the same time interval as the preceding show date, we assign a value of 1 for time consistency. For example, if an influencer streams a show in the *Evening* on September 8 and another show in the *Evening* on September 10 (with no shows streamed on September 9), we assign a value of 1 for time consistency for the show streamed in the *Evening* on September 10.

If multiple shows are streamed on the current date, each show is compared with those from the most recent show date. Conversely, if multiple shows were streamed on the preceding show date, the current show is compared with all the shows from the preceding show date to determine time consistency.

For example, suppose an influencer streams a show in the *Evening* on September 10, two shows on September 11−one in the *Afternoon* and one in the *Evening*, and a show in the *Afternoon* on September 14 (with no shows on September 12 or September 13):

a) the afternoon show on September 11 receives a time consistency value of 0 because no afternoon show was streamed on the previous show date (September 10);

b) the evening show on September 11 receives a time consistency value of 1 because it matches the time interval of the show streamed on the previous show date (September 10);

c) the afternoon show on September 14 receives a time consistency value of 1 because an afternoon show was previously streamed on September 11, the most recent show date.

This logic is applied across all the shows streamed by the same influencer to determine time consistency for each observation.

B.2. Measurements of Instrumental Variables

DayRecurrenceCount is the instrumental variable used for the endogenous variable, *DayConsistency*. It measures the number of times the focal influencer streamed on the same day over the prior four weeks. For example, if an influencer streams on Mondays in Week 1, 2, and 4, but not in Week 3, then in Week 5, the DayRecurrenceCount for Monday is 3. This same logic is applied for the subsequent weeks, and DayReccurenceCount reflects the number of times the influencer streamed on the same day of the week within the most recent four weeks.

TimeIntervalRecurrenceCount is the instrumental variable for the endogenous variable, *TimeConsistency*. It measures the number of times the focal influencer streamed during the same time interval in the prior week. For example, if an influencer streams three shows in the *Morning* in Week 1, then for the shows streamed in the Morning in Week 2, TimeIntervalRecurrenceCount is 3. For subsequent weeks, we continue this comparison on a rolling basis for each observation (e.g., time intervals of the shows in Week 3 are compared with those streamed by the same influencer in Week 2, and so on).

B.3. Fixed Effects Model with Instrumental Variables−First Stage Results

Table B.3.1. Established Influencers

Variables	(1) Day Consistency	(2) Time Consistency
DayReccurenceCount	0.194***	-0.0175***
	(0.00630)	(0.00422)
TimeIntervalRecurrenceCount	0.0467***	0.0775***
	(0.00379)	(0.00357)
Monday	-0.00422	-0.00776
	(0.0115)	(0.0118)
Tuesday	-0.00620	-0.0156
	(0.0104)	(0.0119)
Wednesday	0.00645	-0.000977
	(0.0105)	(0.0108)
Thursday	0.00716	-0.00682
	(0.0104)	(0.0115)
Friday	0.00285	0.0106
	(0.0108)	(0.0113)
Saturday	-0.00297	0.00731
	(0.0111)	(0.0112)
Night	0.0784***	-0.167***
	(0.0215)	(0.0320)
Morning	0.0314**	-0.0489**
	(0.0142)	(0.0204)
Afternoon	0.0209**	-0.0507***
	(0.00988)	(0.0148)
Spillover	-0.000755	0.000830
	(0.000968)	(0.000989)
Log(ShowDuration)	-0.00740	0.0497***
	(0.00830)	(0.0113)
Log(ProductVariety)	0.00388	0.000230
	(0.00846)	(0.00800)
Constant	0.0978	0.0755
	(0.0701)	(0.0961)
Observations	14,454	14,454
R-squared	0.245	0.140
Number of influencers	347	347
Holiday Dummy	Yes	Yes
Week Dummy	Yes	Yes

Standard errors in parentheses are clustered at the influencer level.
**** p<.01, ** p<.05, * p<.1*

Table B.3.2. Top Influencers

Variables	(1) Day Consistency	(2) Time Consistency
DayReccurenceCount	0.199***	-0.00717
	(0.0178)	(0.0105)
TimeIntervalRecurrenceCount	0.0688***	0.0928***
	(0.0116)	(0.0149)
Monday	-0.0835	0.0132
	(0.0585)	(0.0334)
Tuesday	-0.0465	-0.0282
	(0.0513)	(0.0306)
Wednesday	-0.0269	0.0198
	(0.0488)	(0.0310)
Thursday	-0.0566	-0.00163
	(0.0460)	(0.0383)
Friday	-0.0736	-0.0214
	(0.0488)	(0.0353)
Saturday	-0.118*	-0.0191
	(0.0596)	(0.0304)
Night	0.173***	-0.232**
	(0.0614)	(0.0936)
Morning	0.00424	-0.0805
	(0.0452)	(0.0591)
Afternoon	0.0134	-0.0843
	(0.0348)	(0.0564)
Spillover	0.000469	-0.000195
	(0.00453)	(0.00280)
Log(ShowDuration)	-0.0309	0.0208
	(0.0341)	(0.0259)
Log(ProductVariety)	0.0405	-0.0105
	(0.0587)	(0.0300)
Constant	0.146	0.334*
	(0.205)	(0.183)
Observations	1,257	1,257
R-squared	0.257	0.137
Number of influencers	51	51
Holiday Dummy	Yes	Yes
Week Dummy	Yes	Yes

Standard errors in parentheses are clustered at the influencer level.
**** p<.01, ** p<.05, * p<.1*

B.4. Results for Show Outcomes Model without Endogeneity Correction

The table below presents results without endogeneity correction for both established influencers and top influencers. All the analyses were conducted using the "xtreg, fe (cluster)" function in Stata 17, with standard errors clustered at the influencer level. Compared to the results in Table 5, the magnitudes and directions of the key independent variables are lower and inconsistent. Furthermore, the significance levels also change, suggesting the robustness of our endogeneity correction results.

	Established influencers		Top influencers	
	(1)	(2)	(3)	(4)
	Log(ShowViewership)	Log(ShowSales)	Log(ShowViewership)	Log(ShowSales)
Monday	-.023*	-.02	-.039	.005
	(.013)	(.026)	(.044)	(.116)
Tuesday	-.034**	-.038	-.049	-.006
	(.013)	(.03)	(.04)	(.118)
Wednesday	-.074***	-.07**	-.114***	-.138
	(.014)	(.03)	(.037)	(.139)
Thursday	-.068***	-.069**	-.026	.057
	(.013)	(.03)	(.045)	(.146)
Friday	-.04***	-.022	-.045	-.081
	(.013)	(.025)	(.042)	(.126)
Saturday	-.029**	-.043	.007	-.176
	(.012)	(.029)	(.042)	(.168)
Night	-.168***	-.008	-.278	-.356
	(.049)	(.087)	(.204)	(.313)
Morning	-.24***	.042	-.232***	-.218
	(.045)	(.084)	(.073)	(.214)
Afternoon	-.176***	-.094*	-.066	-.091
	(.031)	(.049)	(.071)	(.163)
Spillover	.005**	.007**	.005	.001
	(.002)	(.003)	(.004)	(.007)
DayConsistency	.011	.027	-.041	.182
	(.015)	(.026)	(.033)	(.129)
TimeConsistency	-.036***	-.054*	.022	-.098
	(.014)	(.029)	(.037)	(.078)
ShowDuration	1.039***	1.353***	1.08***	1.379***
	(.031)	(.054)	(.048)	(.15)
ProductVariety	.039	.476***	.003	1.098***
	(.028)	(.077)	(.028)	(.338)
Constant	2.014***	-2.312***	3.047***	-3.55***
	(.242)	(.454)	(.374)	(.938)
Observations	14,454	14,454	1,257	1,257
R-squared	.596	.455	.663	.592
Holiday Dummy	Yes	Yes	Yes	Yes
Week Dummy	Yes	Yes	Yes	Yes

Standard errors in parentheses are clustered at the influencer level.
**** p<.01, ** p<.05, * p<.1*

B.4. Results of the Fixed Effects Model with Instrumental Variables by Using xtivreg2 syntax in Stata.

	Established influencers		Top influencers	
	(1)	(2)	(3)	(4)
	Log(ShowViewership)	Log(ShowSales)	Log(ShowViewership)	Log(ShowSales)
Monday	-0.0226	-0.0206	-0.0414	-0.00112
	(-1.69)	(-0.78)	(-0.93)	(-0.01)
Tuesday	-0.0331*	-0.0371	-0.0482	-0.00357
	(-2.47)	(-1.21)	(-1.17)	(-0.03)
Wednesday	-0.0737***	-0.0711*	-0.112**	-0.135
	(-5.15)	(-2.22)	(-3.14)	(-0.95)
Thursday	-0.0671***	-0.0699*	-0.0248	0.0592
	(-4.90)	(-2.25)	(-0.58)	(0.41)
Friday	-0.0414**	-0.0238	-0.0504	-0.0920
	(-3.24)	(-0.95)	(-1.27)	(-0.68)
Saturday	-0.0297*	-0.0442	-0.00108	-0.193
	(-2.48)	(-1.55)	(-0.03)	(-1.04)
Night	-0.142*	0.0112	-0.282	-0.359
	(-2.51)	(0.11)	(-1.38)	(-1.12)
Morning	-0.230***	0.0484	-0.233***	-0.218
	(-5.23)	(0.59)	(-3.30)	(-0.97)
Afternoon	-0.167***	-0.0880	-0.0679	-0.0939
	(-5.45)	(-1.77)	(-1.01)	(-0.55)
Spillover	0.00487*	0.00723*	0.00525	0.00111
	(2.32)	(2.23)	(1.28)	(0.16)
DayConsistency	0.00244	0.0509	-0.105	0.0458
	(0.05)	(0.63)	(-1.10)	(0.32)
TimeConsistency	0.0540	0.0110	0.000795	-0.128
	(0.72)	(0.08)	(0.00)	(-0.36)
Log(ShowDuration)	1.033***	1.348***	1.079***	1.376***
	(31.85)	(23.65)	(23.02)	(8.58)
Log(ProductVariety)	0.0386	0.475***	0.00597	1.105**
	(1.37)	(6.21)	(0.20)	(3.18)
Observations	14,449	14,449	1,255	1,255
R-squared	0.594	0.454	0.662	0.59
Holiday Dummy	Yes	Yes	Yes	Yes
Week Dummy	Yes	Yes	Yes	Yes
t statistics in parentheses				
* p<0.05	** p<0.01	*** p<0.001		
Diagnostics				
Under-identification test	145.897	145.897	18.528	18.528
Chi-square P-value	0.000	0.000	0.000	0.000
Weak Identification Test				

Cragg-Donald Wald F statistic	594.525	594.525	37.373	37.373
Kleibergen-Paap rk Wald F statistic	204.456	204.456	23.2	23.2
Hansen J statistic	0.000	0.000	0.000	0.000

The additional diagnostic tests also confirm that the instrumental variables are strong and valid.

B.6. Model Specification and Estimation Results Using *SalesQuantity* as a Measure of Show Performance

Model Specification:

$$\log(SalesQuantity_{itd}) = \alpha_i + \beta_0 + \sum_{n=1}^{n=6} \beta_n DayofWeek_{itd} + \sum_{n=7}^{n=9} \beta_n TimeofDay_{itd} + \beta_{10} Spillover_{itd} + \beta_{11} DayConsistency_{itd} + \beta_{12} TimeConsistency_{itd} + \beta_{13} \log(ProductVariety_{itd}) + \beta_{14} \log(ShowDuration_{itd}) + \sum_{n=15}^{n=22} \beta_n WeekDummy_{id} + \beta_{23} HolidayDummy_{id} + \epsilon_{itd}$$

We address the endogeneity issue arising from scheduling consistency using the same set of instrumental variables. Specifically, *DayReccurenceCount* and *TimeIntervalRecurrenceCount* increase influencers' likelihood to maintain scheduling consistency but do not directly impact the sales quantity in the current shows.

Estimation Results:

	Established influencers	**Top influencers**
	(1)	(2)
	Log(SalesQuantity)	Log(SalesQuantity)
Monday	.001	-.006
	(.025)	(.13)
Tuesday	.005	-.012
	(.026)	(.101)
Wednesday	-.032	-.066
	(.029)	(.129)
Thursday	-.044*	.092
	(.026)	(.138)
Friday	-.005	-.09
	(.023)	(.132)
Saturday	-.028	-.296*
	(.024)	(.167)
Night	-.025	-.3
	(.094)	(.299)
Morning	-.021	-.254
	(.072)	(.214)
Afternoon	-.087*	.017
	(.047)	(.139)
Spillover	.007**	-.004
	(.003)	(.007)
DayConsistency	-.021	-.079
	(.08)	(.141)
TimeConsistency	.064	.075
	(.124)	(.374)

Log(ShowDuration)	1.194***	1.234***
	(.053)	(.18)
Log(ProductVariety)	.508***	1.049***
	(.057)	(.372)
Constant	-5.455***	-6.049***
	(.396)	(1.137)
Observations	14,454	1,257
Pseudo R^2	.z	.z
Holiday Dummy	Yes	Yes
Week Dummy	Yes	Yes

Standard errors in parentheses are clustered at the influencer level.
**** p<.01, ** p<.05, * p<.1*

Appendix C Supplementary Materials for Chapter 4

C.1. Proof of Proposition 1.

Second-period equilibrium conversion by influencer's effort:

$$\frac{\partial \pi_{i2}}{\partial e_{i2}} = \gamma np - 2ce_{i2} = 0$$

Solving equilibrium effort from the above first-order condition,

$$e_{i2} = \frac{\gamma np}{2c}$$

First-period equilibrium conversion by influencer's effort

We solve the problem through the first order condition to obtain first-period optimal price. The optimal price is conditional on the predetermined commission rate.

$$\frac{\partial \pi_i}{\partial e_{i1}} = \frac{\partial \pi_{i1}}{\partial e_{i1}} + \frac{\partial \pi_{i2}}{\partial e_{i1}}$$
$$= \gamma np - 2c_i e_{i1} + \gamma np + \gamma hn \cdot np = 0$$

From the above first-order condition, we can solve equilibrium effort.

$$e_{i1} = \frac{\gamma np}{2c_i}(2 + hn)$$

C.2. Proof of Proposition 2.

First period optimal commission for brand:

Substitute $e_{i2} = \frac{\gamma np}{2c}$ and $e_{i1} = \frac{\gamma np}{2c}(2 + hn)$ into brand objective function, we have:

$$\pi_b = \pi_{b1} + \pi_{b2}$$
$$= \rho(1-n)p + (1-\gamma)\left(\rho + \frac{\gamma np}{2c}(2+hn)\right)np$$
$$+ \left(\rho + h\left(\rho + \frac{\gamma np}{2c}(2+hn)n\right)\right)(1-n)p$$
$$+ (1-\gamma)\left(\rho + h\left(\rho + \frac{\gamma np}{2c}(2+hn)n\right) + \frac{\gamma np}{2c}(2+hn) + \frac{\gamma np}{2c}\right)np$$

Take first order condition with respect to γ, we have:

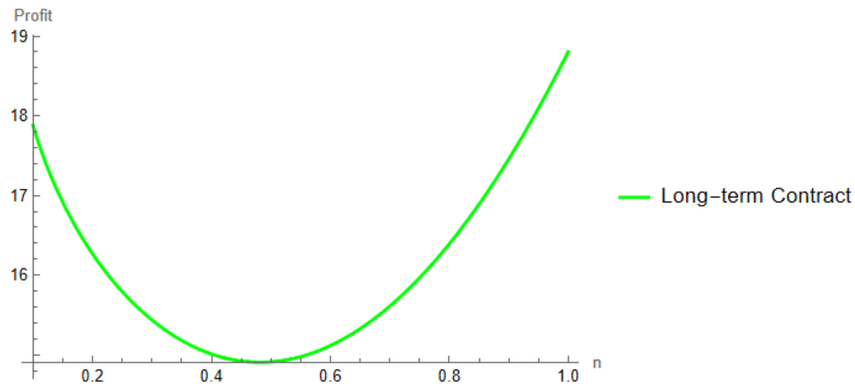
$$\frac{\partial \pi_b}{\partial \gamma} = (-1)\left(\rho + \frac{\gamma np}{2c}(2+hn)\right)np + (1-\gamma)\left(\frac{np}{2c}(2+hn)\right)np$$
$$+ h\left(\frac{np}{2c}(2+hn)n\right)(1-n_i)p$$
$$+ (-1)\left(\rho + h\left(\rho + \frac{\gamma np}{2c}(2+hn)n\right) + \frac{\gamma np}{2c}(2+hn) + \frac{\gamma np}{2c}\right)np$$
$$+ (1-\gamma)\left(h\left(\frac{np}{2c}(2+hn)n\right) + \frac{np}{2c}(2+hn) + \frac{np}{2c}\right)np = 0$$

Simplify the equation, we obtain:

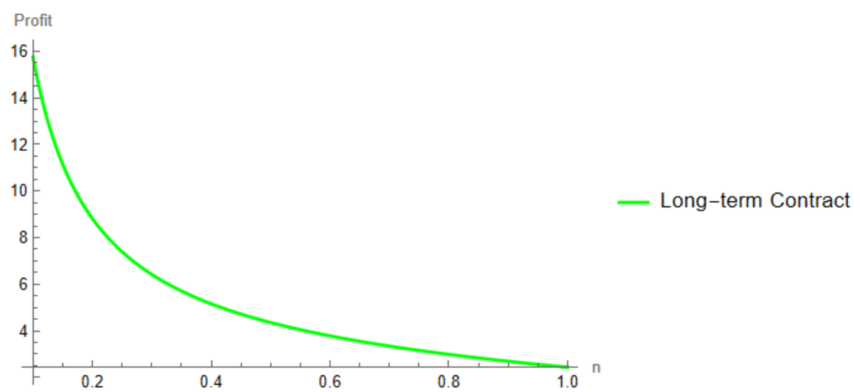
$$\gamma = \frac{1}{2} \cdot \left[1 + \frac{h(2+hn)(1-n)}{1+(2+hn)^2} - \frac{\rho}{\frac{np}{2c}}\left(\frac{(2+h)}{1+(2+hn)^2}\right)\right]$$

C.3. Proof of Proposition 3.

For established brands with high average price: simulation results with the following parameters: $\rho = 0.9;\ p = 9; c = 4; h = 1$

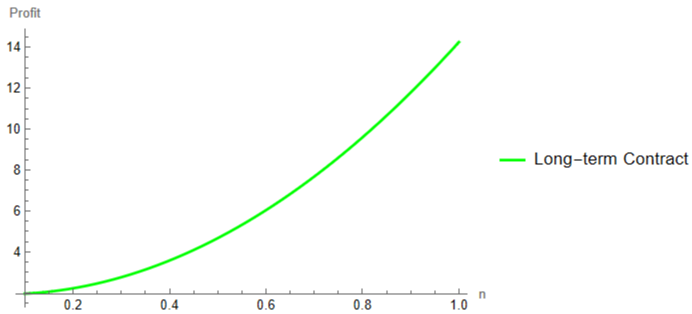


For established brands with low average price: simulation results with the following parameters: $\rho = 0.9;\ p = 1; c = 4; h = 1$

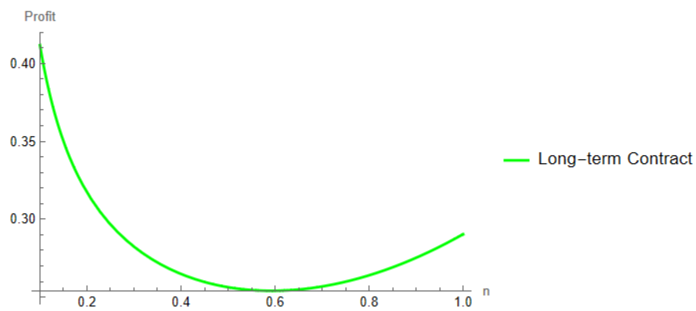


C.4. Proof of Proposition 4.

For emerging brand with high average price: simulation results with the following parameters:$\rho = 0.1;\ p = 9; c = 4; h = 1$

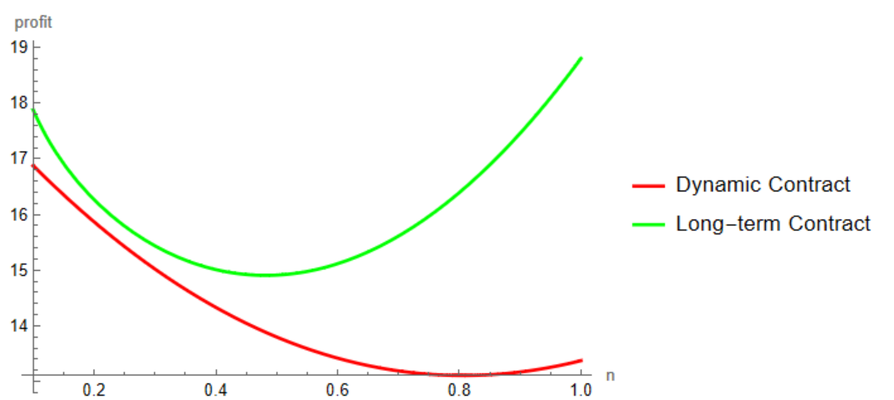


For emerging brand with low average price: simulation results with the following parameters: $\rho = 0.1;\ p = 1; c = 4; h = 1$

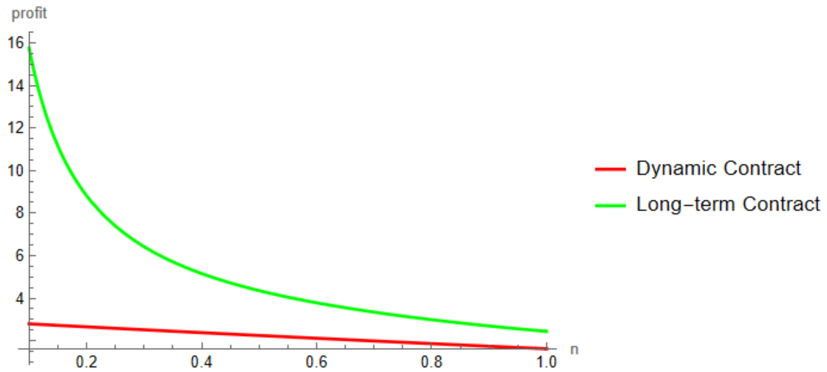


C.5. Proof of Proposition 5.

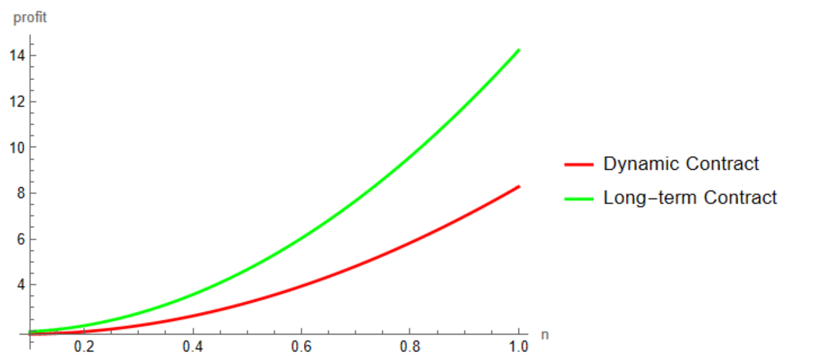
For established brands with high average price: simulation results with the following parameters: $\rho = 0.9;\ p = 9; c = 4; h = 1$



For established brands with low average price: simulation results with the following parameters: $\rho = 0.9;\ p = 1; c = 4; h = 1$



For emerging brand with high average price: simulation results with the following parameters:$\rho = 0.1;\ p = 9; c = 4; h = 1$



For emerging brand with low average price: simulation results with the following parameters: $\rho = 0.1;\ p = 1; c = 4; h = 1$