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**MULTI-CHANNEL MANAGEMENT AND
PLATFORM OPERATIONS IN THE
DIGITAL ERA**

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PhD

The Hong Kong Polytechnic University

2022

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**Multi-Channel Management and Platform Operations in the
Digital Era**

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of
Philosophy

May 2022

CERTIFICATE OF ORIGINALITY

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Abstract

Nowadays, e-commerce becomes more and more important for multi-channel operations with the rapid development of sophisticated information technologies. As a result, multi-channel operations have expanded to cover various types of online channels, such as the firms' official websites, mobile apps, and third-party platforms. When the multi-channel operations strategy is adopted, channels interact with each other. Considering the impacts of cross-channel influences, channel selection and coordination are complicated but crucial for multi-channel operations. On the other hand, towards facilitating connection and collaboration among parties, platforms of all kinds are very popular. From the perspective of platform functions, they can be classified into product selling platforms (e.g., e-commerce platforms) and service platforms (e.g., social media platforms). In this situation, in the e-commerce era, it is important for firms to strategically implement platforms to improve operations (e.g., generating higher profit or social welfare). Motivated by the importance of multi-channel operations and platform management, this thesis aims to: (i) Investigate the impacts of cross-channel influences on the mobile-app-website and e-platform-website multi-channel operations; (ii) explore the optimal channel structure and coordination contract for multi-channel operations; (iii) examine the optimal implementation of social media platform to launch advertisement (including the probable case of negative publicity). In this thesis, a chapter is devoted to each of the above major topics under exploration. Moreover, to analyze the proposed issues, the analytical modeling approach is adopted to characterize different research problems and derive theoretically solid findings.

Regarding aim (i), we first consider the case where an e-tailer sells products in a mobile-app (MA)-website (WS) dual channel newsvendor supply chain. In this dual channel supply chain, the e-tailer can adopt risk pooling (by aggregating the demands from MA and WS channels together) and invest in forecast-enhancement technology (FET) to improve inventory management. Considering the impacts of cross-channel influences, demand from one online channel may increase (called *channel reinforcement effect*) or decrease the demand from the other online channel (called the *channel cannibalization effect*). The influences are not necessarily symmetric. First, by building the analytical models and solving the respective optimization problems, we derive the optimal inventory decision and investment level for FET. We uncover that when the magnitude of cross-channel influence increases, the impacts on the optimal inventory decision, as well as performances of the e-commerce

supply chain and its agents, vary greatly (depending on four different “model cases”); interestingly, it has no impact on the optimal FET decision. In addition, we examine the supply chain coordination challenge in this MA-WS dual channel and explore the impacts of cross-channel influences under different contracts.

Second, in order to explore the impacts brought by cross-channel influences in dual channel and the optimal channel selection and coordination problem (i.e., aim (ii)), we consider the case where an e-tailer can sell products through the e-platform and/or direct selling channel. We build analytical models to explore “when” an e-tailer should choose “which” channel structure and how to coordinate these dual channels with the consideration of cross-channel influences. Based on the commonly-observed industrial practices, we derive the optimal e-platform service contract which is a revenue-sharing plus fixed fee (RSF) service contract. Then, we establish the conditions under which the e-tailer’s optimal channel selection choice will also be optimal for the e-platform systems.

Third, platforms can be adopted to improve e-commerce operations by providing services, in addition to playing as a sales channel. Therefore, we pay attention to the advertising service that social media platforms (SMPs) provide for luxury fashion brands (LFBs) to explore the optimal implementation of service platforms (i.e., aim (iii)). Today, social media platform (SMP) advertising is common for luxury fashion brands (LFBs). Regarding the implementation of SMPs, we consider the scenario in which luxury fashion firms can better identify different groups of consumers and may advertise to them with tailored content (i.e., adopting the customized advertising strategy) at a cost. In this part of the thesis, we explore the optimal SMP-based advertising strategies for a profit-maximizing LFB. We find that whether or not the SMP-based customized advertising strategy outperforms the non-customized strategy depends on the snobbishness level as well as the associated fixed costs. In addition, we analytically uncover that if the snobbishness level is relatively high, implementing controversial advertisements which create negative publicity will be optimal.

To conclude, realizing the significance of multi-channel operations and platform management in the e-commerce age, this thesis conducts three analytical studies to uncover different facets of the associated challenges. The analytical findings and managerial insights generated from this thesis not only contribute to the literature, but also provide valuable guidance for industrial managers who are engaged in platform operations. Last but not least, future research is discussed and hence this thesis also inspires further studies in related directions.

Publications arising from the thesis

Journal Publications and Working Papers

1. Wen, X., **Siqin, T.** (2020). How do product quality uncertainties affect the sharing economy platforms with risk considerations? A mean-variance analysis. *International Journal of Production Economics*, 224, 107544.
2. **Siqin, T.**, Choi, T.M., Chung, S.H., Wen, X. (2022). Platform operations in the industry 4.0 era: Recent advances and the “3As framework”. *IEEE Transactions on Engineering Management*, 10.1109/TEM.2021.3138745.
3. **Siqin, T.**, Choi, T.M., Chung, S.H. (2022). Optimal e-tailing channel structure and service contracting in the platform era. *Transportation Research Part E*, 10.1016/j.tre.2022.102614.
4. Choi, T.M., **Siqin, T.**, Wen, X, Chung, S.H. (2022). Cross-channel influences in mobile-app-website e-commerce newsvendor supply chains. Under review.
5. **Siqin, T.**, Sethi, S.P., Chung, S.H., Choi, T.M. (2022). Social platform advertising for luxury fashion brands: Customization and negative publicity. Working paper.

Conferences

1. **Siqin, T** (presenter) (with Xu, X, Choi, T.M., Chung, S.H.). Seeking survivals under Covid-19: The WhatsApp shopping service operations. *MSOM Conference 2021*, Indiana, USA (online), 7-10 June, 2021.
2. **Siqin, T** (presenter) (with Choi, T.M., Chung, S.H., Sethi, S.P.). Social platform advertising for luxury fashion brands: Customization and negative publicity. *INFORMS Annual Conference 2021*, Anaheim, CA, USA (online) 24-27, October, 2021.
3. **Siqin, T** (presenter) (with Choi, T.M., Chung, S.H., Wen, X.). Platform operations in the industry 4.0 era: Recent advances and the “3As framework”. *The 32nd Annual POMS Conference*, Orlando, FL, USA (online), 23-24, April, 2022.

Acknowledgements

Suddenly, it's time to say goodbye to my PhD journey. Throughout my three-year journey at PolyU, I have received a great deal of support.

First, I would like to express my deepest gratitude to my supervisor Dr. Nick Sai-Ho Chung. His constant support and valuable guidance always help me find a clear way to fix problems when I was confused with academics. I would also like to express my deepest appreciation to my supervisor Professor Jason Tsan-Ming Choi. I could not have started the three-year study without the opportunity that he gave to me. During my three-year study, Prof. Choi always gave me the greatest trust, support, and patience, which encourage me to never give up. I was deeply inspired by Prof. Choi's passion for academics and his hard-working attitude toward work. I will always remember what he taught me: "doing research is a hobby, not just a job". I will try to follow in his footsteps to become a researcher with true passion and do good research. Besides, I am deeply grateful to my supervisor Dr. Windy Xin for her valuable guidance and comments on my research, which help me a lot when I got into trouble in research, especially in my first work. Apart from academics, my supervisors provide tremendous support and guidance in my life. I have learned a lot from them, e.g., stepping out of the comfort zone (i.e., being brave), being responsible for duties, and accepting myself. I am very fortunate that I can be their student.

Second, special thanks to my fellow team members. They formed an integral part of my PhD study. It was enjoyable for having inspiring discussions and working with them. I benefited a lot from their opinions on the ideas, methodologies, and analyses of the research. Especially, I would like to thank my "academic sisters" Katy and Kelly who grew up with me together. I indeed have learned a lot from them, which includes not only the serious academic spirit but also the optimistic attitude toward life. I feel very glad that I can accompany and study with them, and have good friends like them.

Third, I would like to extend my sincere thanks to my parents and husband (Mr. Xin Ge). They always support my decisions unconditionally and provide with me the warmest love. I love them forever.

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Chapter 1 Introduction

1.1 Background

Multi-channel operations are developing fast in recent years due to the popularity of e-commerce. During the Covid-19 pandemic, city lockdown and other epidemic prevention policies further accelerate the growth of e-commerce. As reported, owing to the Covid19 pandemic, increases of e-commerce in the US are over one hundred billion US dollars in 2020 and \$164.5 billion in 2021¹, respectively. It is observed that giant retail brands, such as P&G, MARS, IKEA, and Adidas, have all operated in the multi-channel mode in order to respond to the highly variable and diversified consumers' shopping preferences. Multi-channel operations refer to the retail operations where sellers "branch out" their original single selling channel (e.g., physical stores) to other channels, such as the official website, mobile app, and electronic platform (e-platform) (Schoenbachler & Gordon, 2002). With the wide adoption of e-platform and mobile electronic communication all over the world, multi-channel operations come into a new era that embraces more diverse online sales channels. Some well-known retailers, such as home goods retailer IKEA, have deployed multi-channel operations and incorporated the website, e-platform and mobile app as their selling channels². Specifically, IKEA has switched to multi-channel operations and expanded its retailing channel from physical store only operations to incorporate the website, then the mobile app. Under the multi-channel operations, IKEA's consumers can conveniently look through the information about products and make orders through its official website or the IKEA Store app instead of physically visiting the store. According to a report published at Statista.com, online sales of IKEA grew by around 10% in 2021, and the net sales of IKEA.com is estimated to increase and reach over \$10,000 million in 2022³. Therefore, considering the importance of e-commerce, how to optimally design the multi-channel operations strategies is critical for retailers.

Official website, mobile apps, and third party e-platform are trendy online channels that are widely adopted by firms. (Bang et al., 2013). At the early stage of e-commerce, firms usually developed

¹ <https://www.digitalcommerce360.com/article/coronavirus-impact-online-retail/>

² <https://www.clickz.com/four-brands-leading-the-way-in-multichannel-marketing/91969/>

³ <https://www.statista.com/forecasts/1218317/ikea-revenue-development-ecommercedb>

official website for consumers to conveniently visit. Development of information technology and upgrade of e-commerce technologies have spawned the model of online sales on mobile terminals and third-party e-platforms. Mobile commerce is becoming growingly popular under the new information technology era. According to a report published at Statista.com, the revenue of mobile commerce kept increasing from 2013 to 2020 in the United State, reaching over 700 billion USD in 2025⁴. E-platforms act as a marketplace for e-tailers to sell their products through the well-established e-commerce infrastructure. It is similar to a big center that offers e-commerce transactions from different brands altogether. Due to the integration of brand transactions, e-platforms always have a wider market base, which would naturally attract firms to join. For instance, well-known sportswear seller Adidas is collaborating with e-platforms (e.g., Amazon, eBay, and Tmall) to sell products online. Despite the commonality of e-platforms and mobile apps is online, they are two different types of channels to sell products. Differences between the e-platform and the mobile app can be depicted from the following aspects (i) accessibility for consumers to use (ii) information technology requirements for users, (iii) channel coordination for sellers. Based on the peculiarity of these two channels, it is hence crucial to explore how characteristics of mobile channel and e-platform (e.g., features of mobile app) can affect consumer's behavior and the online seller's operations strategies (e.g., pricing strategy and promotion effort) to sell products.

With the advancement of technologies, modern business operations have entered the digital era (Lakemond et al., 2021), and the sharing economy has been established. Toward facilitating the connection and collaboration among various parties in the sharing economy, platforms of all kinds (from social media, e.g., WhatsApp (Xu et al., 2021), to giant e-commerce platforms, e.g., Amazon) are now very popular in practice⁵. In fact, as reported⁶, six of the ten most valuable brands worldwide have adopted the platform-based business mode in 2021, including Apple, Amazon.com, and Google. This shows the importance of platforms for the modern economy. Platform operations have thus attracted extensive research interests from academia (Chen et al., 2020). In addition to product selling platforms that play as marketplaces to sell products, service platforms, such as social media platforms,

⁴ <https://www.statista.com/statistics/249855/mobile-retail-commerce-revenue-in-the-united-states/>

⁵ In order to explore how the advanced technologies improve the operations of platforms, the author proposes a “3As” framework, which is presented in Appendix I.

⁶ <https://brandirectory.com/rankings/global/> accessed on 20 September 2021.

have been integrated into online selling. For instance, advertising on social media platforms is a hot topic in practice. This leads us to explore the impacts of service platforms on e-commerce and the strategy for sellers to adopt service platforms.

1.2 Research Objectives

Motivated by the prevalence of multi-channel and platform operations, the purpose of this thesis study is to investigate the multi-channel operations with the adoption of the mobile app and e-platform online channels, and examine the optimal implementation of platforms in the e-commerce age. To be specific, this doctoral thesis has the following main objectives explored by analytical modeling analyses:

1. With respect to the multi-channel operations, this work is to analytically analyze the optimal channel structure considering several online channels, such as the direct selling channel (website), mobile apps, and platforms. Specifically, we characterize features of different channels using models and examine performance of them.
2. From the perspective of channel interaction in multi-channel operations, this work incorporates cross-channel influences (i.e., positive or negative) into consideration and explores impacts of them on different types of multi-channel operations.
3. From the perspective of platform operations, this work jointly considers two functions of platforms, the product selling oriented platforms and service platforms in the e-commerce era. We aim to explore the optimal strategy to adopt these two types of platforms (i.e., e-platform in multi-channel operations and advertising on social media platforms) and how they can improve the multi-channel and e-commerce operations.

In order to verify the robustness of major findings and generate deeper insights, we incorporate various issues (such as supply chain coordination, consumer surplus, and budget constraints) as extensions of major questions in each chapter. The influences of the corresponding mentioned issues on multi-channel operations and platform performances will be discussed as well.

1.3 Contribution Statement

Multi-channel operations and the platform management become increasingly crucial in the 4.0 era. During the Covid-19 pandemic, owing to the restriction of government policy on physical activities, it is of the greatest importance that this thesis examines the multi-channel operations with diverse online channels and platform operations considering the impacts of disruptive technology. In the existing literature, the multi-channel operations and platform management have been studied for plenty of years. However, how multi-channel operations can be coordinated considering the cross-channel impacts of different online channels is still under-explored. In addition, how platform can be implemented with the help of disruptive technology in e-commerce has not been well-explored. Therefore, this thesis contributes to the existing literature as follows.

First, from the perspective of dual-channel coordination when both the website and mobile app selling channels are implemented, we analytically explore the e-commerce supply chain coordination and the significance of cross-channel influences. To the best of our knowledge, this is the first analytical study which examined inventory management in e-commerce supply chains involving an e-tailer selling through both the WS and MA channels. The magnitudes of cross-channel influences are highlighted and explored under different model settings. Many novel managerial insights are derived analytically regarding to the channel influences strengthen or weaken. These findings not only can contribute to the literature but also advance industrial knowledge on the emerging mobile commerce operations in practice.

Second, in this thesis, we theoretically explore the problem: whether and when an e-retailer should adopt e-platforms as a sales channel by developing the analytical models and proposing an algorithm for determining the optimal channel choice. To the best of our knowledge, this work is the first paper in the literature that studies the use of e-platform services with the consideration of channel influences into the theoretical models. This important feature differentiates this paper from other existing papers, such as Wang et al. (2004) and Ryan (2012), on e-platform operations. Last but not least, we propose a service fee contract to coordinate the ET-PF system according to the definition of coordination proposed in Gan et al. (2005) which aims to achieve flexible system coordination in which both parties obtain profits no less than their reservation profits.

Third, regarding the implementation of platform in e-commerce era, we analytically explore the optimal strategy that adopt the social media platforms to launch customized ads so that to sell products online. To the best of our knowledge, this work is the first study in the literature that analytically examines SMP advertising strategies for LFBs with the considerations of customized advertisement and negative publicity. We interestingly highlight the importance of negative publicity and explain why it is popularly used in practice. However, different from Chatterjee and Zhou (2020) who explore the effect of consumers' dislike on advertisers, we examine that the controversial advertisements are intentionally established by LFBs (i.e., retailers) themselves. Therefore, impacts of negative publicity on retailers' advertising strategies can be generated in this thesis. We also uncover the impact of social influences which is crucial for LFB operations, while under-explored for LFB's advertising strategy. This work also supplements the findings of targeting advertising in Iyer et al. (2005) and contributes to the related scope of study. We believe the research findings uncovered in this study not only contribute to the operations management (OM) literature but also enhance our industrial knowledge regarding the SMP advertising strategies in the digital era.

1.4 Thesis Outline

This work is organized as follows. First, in Chapter 2, this thesis provides a comprehensive review of related literature from three directions: multi-channel operations, e-commerce supply chain management, and supply chain operations with fashionable products. Then, Chapter 3 characterizes the features of mobile app and website channels and builds analytical models to explore the multi-channel operations considering the cross-channel influences. Specifically, the market demand is considered to be uncertain and the newsvendor model based analysis is conducted. Next, incorporating platforms into multi-channel operations, Chapter 4 analytically examines the optimal e-tailing channel structure and channel coordination with the consideration of cross-channel influences. The optimal pricing and channel structure are uncovered in this chapter. Thereafter, with respect to the service function of platforms, Chapter 5 examines the performance of social media platforms in the e-commerce of the luxury fashion industry. Considering the social media platform's ability to provide the customized advertising service for sellers, the optimal platform adoption strategy is explored. At

last, Chapter 6 provides concluding remarks and discusses future research directions. Figure 1.1 is provided to show the thesis outline.

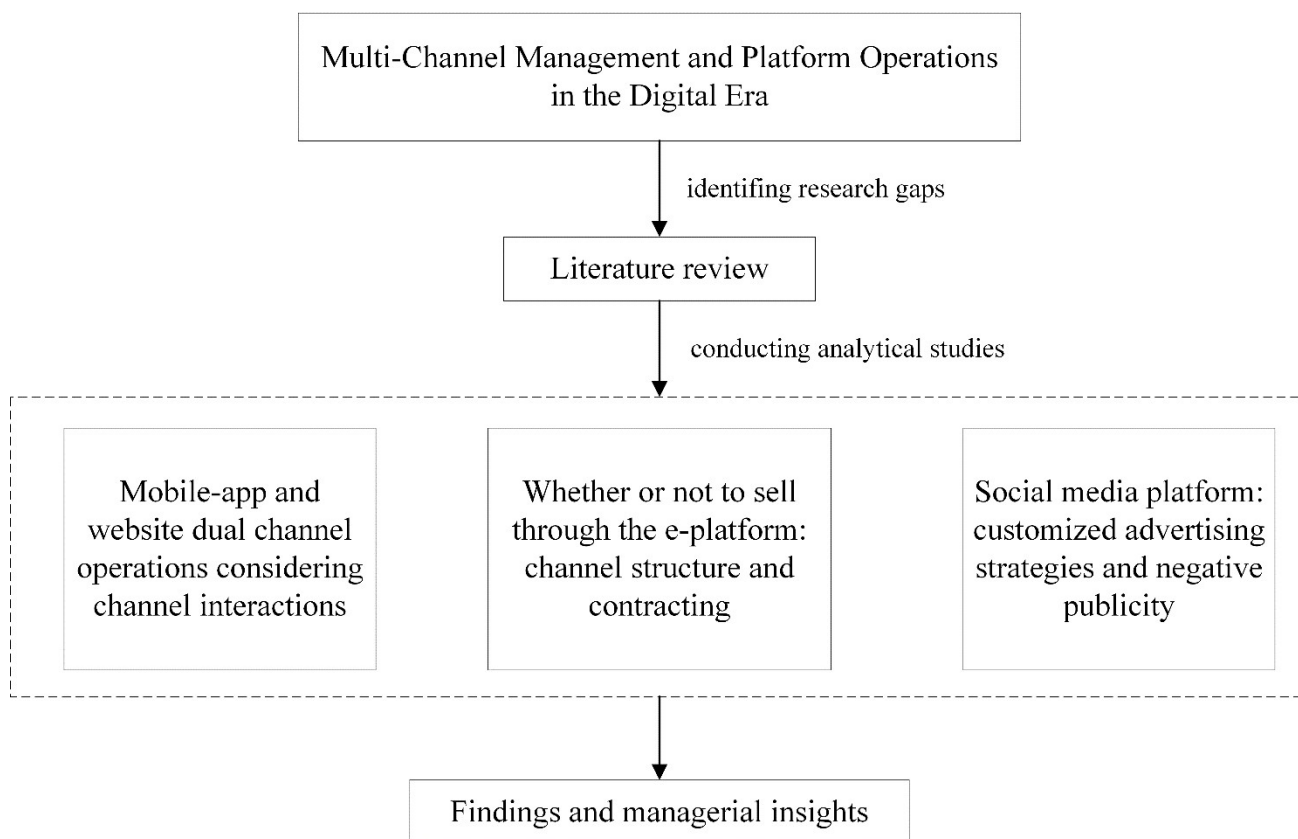


Figure 1.1. Thesis outline.

As a remark, some supplementary information that can facilitate the understanding of the background and major findings is provided in Appendix I. Mathematical proofs of three technical chapters (3, 4, 5) are provided in Appendix II.

Chapter 2 Literature Review

In this chapter, literature that is closely related to this doctoral thesis has been reviewed. First, Chapter 2.1 presents the literature review on multi-channel operations. Specifically, we focus on reviewing the literature that explores the multi-channel operations in e-commerce age, e.g., mobile apps in multi-channel e-commerce (Chapter 2.1.1) and e-platform in multi-channel e-commerce (Chapter 2.1.2). In addition, the cross-channel interactions are introduced in Chapter 2.1.3. Second, studies related to platform operations in the digital era have been reviewed in Chapter 2.2. Third, e-commerce supply chain management are reviewed in Chapter 2.3 because this doctoral thesis aims to explore the multi-channel operations and platform management under the circumstance of the e-commerce age. Forth, Chapter 2.4 conducts the literature review about supply chain operations for fashionable products as we mainly pay attention to exploring the operations for products that are perishable or of high quality. Specifically, the advertising strategy for fashionable products is introduced in Chapter 2.4.1, and consumer behaviors for luxury fashion products related literature is reviewed in Chapter 2.4.2. Finally, we summarize the research gaps between this doctoral thesis and the reviewed literature in Chapter 2.5 and highlight the contribution of this thesis.

2.1 Multi-channel Operations in the E-commerce Age

The operations of retailing have changed significantly in the past decades due to the “rocket speed” development of Internet technologies. Multi-channel operations play a critical role in channel management which includes various patterns with respect to the channel interactions (Verhoef et al., 2015). The typical multi-channel operations refer to the case in which sellers offer products to customers through channels separately and simultaneously. On one hand, in the supply chain system, the manufacturer delivers products to customers in different channels. For example, Chiang et al. (2003) propose an analytical model to capture consumers’ acceptance of the manufacturer’s direct selling channel with the deployment of direct channel and retail channel simultaneously. Afterwards, Geng & Mallik (2007) examine the role of inventory competition and inventory allocation between a manufacturer’s direct selling channel and retail channel. The authors find that two parties in the supply

chain system could be benefited with a mild capacity constrain. Cai (2010) explores the influences of channel selection between single-channel and dual channel supply chains on achieving the coordination of it. On the other hand, strategies of multi-channel operations for single sellers are critical and timely. For example, whether the seller should provide a lower price in between “online and store” channels to consumers, which is named “the self-matching strategy”, has been investigated in order to improve the multi-channel retailers’ profit (Kireyev et al., 2017). Zhang (2009) analytically addresses that “when and how” a traditional retailer should implement multichannel operations to sell products with the consideration of advertising store’s selling price in online channel.

In addition, interactions of multiple channels with the focal point on their synergies, which are commonly called omni-channel operations, are prevalent. Gao and Su (2018) focus on the implementation of self-order technologies in restaurants. They explore the interactions of online and offline ordering channels and the corresponding influences on the restaurant’s employment level. Showrooming and buy-online-and-pick-up-in-store (BOPS) represent the two popular cases of omni-channel operations. Operational strategies are explored in order to improve the seller’s and supply chain systems’ payoffs under these two cases (Gao and Su, 2017; Jing 2018). Different from the research above, this work focuses on the demand uncertainty of the multi-channel operations and its influences on the seller’s optimal decisions. Moreover, it is rather crucial for the seller to incorporate the uncertain of demand into multi-channel operations due to the high levels of social uncertainty under effects of epidemic.

2.1.1 Mobile-apps in Multi-channel E-commerce

For mobile apps adoption in e-commerce, Gupta and Jain (2014) empirically explore the use of mobile phones in India. Balapour et al. (2020) explore security for mobile apps by using the “communication privacy management” theory. The authors conduct an empirical survey-based study to highlight how the consumers’ “perceived privacy” affects the “perceived security” of mobile apps. Degirmenci (2019) empirically studies how privacy affects the users’ decision on installing or uninstalling mobile apps. A new empirical model is proposed and a conclusion on avoiding excessive use of privacy permissions is obtained. Wen and Zhu (2019) investigate the innovation efforts of mobile platform facing the threat

from a market entry. The authors motivate the study based on the cases of Android and Google. They uncover the strategic implications behind the “value-creation and value-capture” strategies. Wu et al. (2020) examine the influences of mobile security and users’ intention to continuously use the mobile apps. The authors focus on highlighting the role played by the design of “mobile app interface” and “mobile security notification”. All of the above studies are empirical based and focus on the users’ perception towards mobile apps and their security. On the contrary, a few analytical studies are reported. For example, Wang et al. (2018) study the optimal promotion policies and decisions for mobile apps. Katewa and Jain (2020) analytically explore the optimal pricing and quality decisions for mobile applications owned by the system platforms (e.g., Android and IOS) and the app developers. The authors find that the revenue contract affects the quality of mobile apps.

Mobile-apps can play as the selling channel to help retailers sell products in the e-commerce age. There is a small amount of literature that explores this topic. For example, Amrouche et al. (2020) study a multi-channel supply chain system in which an online retailer sells through both the mobile channel and website channel. The authors focus on the optimal pricing strategies. Most recently, Choi (2020b) examines the optimal pricing decisions in an e-commerce supply chain in which both mobile and website channels exist. The author models users’ “privacy concerns” and “e-payment convenience” perceptions and focuses on investigating the impacts of the e-tailer’s risk-aversion on the optimal pricing decisions. The above studies have studied many aspects of mobile apps and related mobile commerce issues. However, they do not focus on critical operational issues such as inventory management (e.g., ordering decisions). This work fills this important gap.

2.1.2 E-platform in Multi-channel E-commerce

E-platforms have been established as a crucial part of e-commerce, especially when e-commerce operations include multiple channels (Gao and Su 2016; Wang et al. 2004; Ryan et al. 2012). The contracting design between e-platforms and vendors has been explored in prior studies. For example, Mantena et al. (2010) study the contracting strategies between platforms and vendors in a competitive market. Shen et al. (2019) examine dual-channel supply chain contracting challenges, in which a manufacturer sells its products to consumers through a traditional retailer and an e-platform seller.

Exploring the optimal contracting between the manufacturer and e-platform, the authors find that a win-win outcome can be achieved when the e-platform simultaneously decides the revenue sharing and slotting fee. Different from Shen et al. (2019), Zennyo (2020) explores the “strategic contracting” decisions in e-commerce service platforms. The author studies the wise implementation of a mixed contract, which includes the use of “agency and wholesale contracts”. In addition to the contract design between the e-platform and vendors, Tian et al. (2018) explore the optimal strategy for an online retailer to play as the marketplace (i.e., e-platform). The authors find that it is optimal for the online retailer to take the role of the marketplace when the products are seriously differentiated. Choi (2020b) studies the integration of mobile apps platform and online-website sales channels for e-tailers. The authors uncover how “privacy concerns, e-payment convenience, and channel relationship” affect the optimal decision and supply chain performance. Ha et al. (2021) investigate the agency mode and reselling mode of the online platform provided to the manufacturer. The authors find that the hybrid model can affect the shift of sales between two channels. Most recently, Ha et al. (2022) examine the situation in which the manufacturer should encroach an agency selling channel on an e-platform. The authors find that encroachment and information sharing are “complementary”. Platforms are a central part of this work. However, different from the above studies, we focus on the product selling service that the e-platform provides to the e-tailer, and further explore whether and when an e-tailer should work with the e-platform. This is different from the above reviewed prior studies.

2.1.3 Cross-channel Interactions in Multi-channel Operations

This work also studies channel interactions for e-commerce. Most prior studies focus on online-offline interactions (e.g., see Gao and Su. 2016) which include studies covering showrooming (Bell et al. 2015, Bell et al. 2017; Zhang et al. 2020a) and “buying-online-picking-up-offline operations” (see, e.g., Gao and Su. 2017). However, limited studies study the interactions among diverse online channels. For example, Huang et al. (2016) empirically explore the impacts of channel cannibalization and channel synergy under the website and mobile app dual channel system, and the results show that deploying the mobile app is profitable for the retailer. Park et al. (2020) empirically find that implementing mobile apps to provide products searching and products selling can increase the sales of “tail products”.

For analytical studies, Amrouche et al. (2020) explore the case in which the website channel and mobile channel are integrated together as an “online-channel”. How the presence of mobile channel may increase or decrease the website channel’s demand, and vice versa, is not examined. Choi (2020b) studies channel relationships but the model focuses on privacy concerns and shopping convenience with e-payment. How inventory management is affected and forecast enhancement can be made are both not mentioned. This work contributes to this area of research by providing novel insights and comprehensively discussing the impacts brought by channel relationships on inventory decisions and supply chain performance.

2.2 Platform Operations in the Digital Era

Platform operations are getting more and more important. Many studies in operations management (OM) have explored platform-related business operations for over a decade (Tiwana et al. 2010). For example, Bhargava et al. (2013) examine the optimal starting time and updating of business platforms. Wang et al. (2016) study the “taxi-hailing” service platform and determine the optimal service charging strategy. Bellos et al. (2017) study car-sharing platforms. The authors highlight the role played by “product line design” in the optimal selection of business models. Cachon et al. (2017) explore the service platform operations in which the platform can schedule its own service volume. For two-sided platforms, Kung and Zhong (2017) study the pricing decisions for the “two-sided platform” operations in the logistics sector. Sun et al. (2019) examine the “ride-sourcing platforms” and derive the corresponding optimal pricing policies. Bai et al. (2018) study how “on-demand service platform” can be used to effectively match “supply” and “demand”. The authors consider the situation in which consumers in the market are “impatient”. Choi (2020a) explores the financing challenges in a start-up project which is commonly seen in many technological platform development projects. Du et al. (2019) investigate the environmental sustainability related advertising optimization problem with the platform based operations. Zeng et al. (2020) examine the maritime service related platform booking systems. Choi et al. (2020) study the optimal service pricing decisions in “on-demand service platforms”. The authors discover how blockchain technology can be implemented to improve the service operations by better dealing with consumers with different risk attitudes. Shen et al. (2020) study the deployment of

blockchain to build platforms for selling used products. In a similar vein, Cai et al. (2021) explore the use of blockchain based platforms for clearing leftover in a primary market.

In the presence of platforms in the digital era, peer-to-peer (P2P) collaborative consumption is made possible. Chen et al. (2015) examine the P2P information share among “farmers in developing economies”. The authors highlight the power of the e-platform. Jiang et al. (2017) explore the P2P e-marketplace and reveal the influences brought by the “consumer valuation uncertainty”. Choi and He (2019) study how the e-platform can support P2P operations and affect fashion businesses. Wang et al. (2020) analytically explore the P2P product sharing when the seller also enters the “sharing market”. Unlike these studies, this work does not cover P2P product sharing with e-platforms. Instead, we follow the observed industrial practices to study when and whether the e-tailers should hire the e-platform to sell their products and if yes, the optimal e-platform service pricing policies. Compared with Ryan et al. (2012) and Ha et al. (2021), we focus on the channel coordination problem between the e-tailer’s original selling channel and the e-platform with an innovative consideration of channel influences and reveal their impacts.

2.3 E-commerce Supply Chain Management

In e-commerce operations, supply chain management is known to be an important area. In the classic study, Tsay et al. (2004) explore channel conflicts and supply chain coordination in electronic commerce. The authors examine how supply contracting such as wholesale pricing policies can adjust the supplier-buyer relationship to enhance supply chain performance. Besides, several studies explore the supply chain management problems for dual channel operations. For instance, Zhang and Wang (2017) investigate dual channel coordination in supply chains including both the online and offline operations. The authors study the situation with two selling periods and fixed inventory. Ishfaq and Bajwa (2019) study online fulfillment operations for supply chains with dual channels. The authors derive an optimization model and solution scheme to determine the optimal online order fulfillment decisions. Yan et al. (2020) examine the coordination of dual channel supply chain under which the supplier is capital-limited. The authors highlight the challenge associated with retail financing for the online retailer. Recent studies also pay attention to supply chain contracting, information sharing, and

technology application for e-commerce supply chain operations. For example, Zenny (2020) explores the supply chain contracting mechanism between a platform and two competing sellers. The optimal decision on the royalty rate is also found. Gao et al. (2020) find that it is profitable to share the product loss information for an e-commerce supply chain system. Moreover, Li et al. (2021) uncover that implementing blockchain technology may improve consumer surplus and social welfare for e-commerce platforms. Overall, the above studies all explore various important problems associated with e-commerce supply chains. However, the presence of mobile channel and interactions between the mobile channel and website e-commerce are not well explored. This is the research gap that this work bridges.

Product-service supply chains (PSSCs) implies the supply chain operation in which both physical products and service are included. Wang et al. (2015) first define this product service supply chain concept in the popular review paper. In the literature, many studies have considered PSSCs management problems. For instance, with the consideration of free shipping services, Hua et al. (2016) investigate the optimal inventory and pricing decisions in the single-period stochastic inventory problem. Dong et al. (2017) study the electricity supply chain system using tariff-contract with demand uncertainty. Liu et al. (2018) study order distribution in a service supply chain system. The authors consider the fairness issues when allocating the orders. Wang (2018) explores the mean delivery services in the presence of many suppliers. The authors examine whether it is a wise decision to share the logistics services. This work is in line with the concept of PSSCs, we study the e-tailer's product selling with the support e-platform's service.

In addition, supply chain coordination has attracted researchers' attention. For instance, Cachon and Lariviere (2005) examine the supply chain coordination between a supplier and retailers using the revenue-sharing contracts. Taylor (2002) study supply chain coordination using the sales rebate contract. Note that the achievability of supply chain coordination is affected by various factors. For example, Asian and Nie (2014) explore supply chain coordination with the consideration of demand uncertainty and the risk of disruptions. Shi et al. (2019) study the supply chain coordination challenges by considering environmental sustainability issues. Xu et al. (2020) explore the logistics decision in the channel with e-platform and focus on studying the coordination challenge. Most recently, Choi

(2020a) explores the use of “elastic logistics” in a PSSC facing market disruptions. The author uncovers the critical function of elastic logistics in dampening the ripple effect in the PSSC. For more related studies, please refer to the review paper by Wang et al. (2015). This thesis also studies the system coordination in a supply chain while the focal point is on the value of e-platform. This is an under-explored area to which this work aims to contribute to.

2.4 Supply Chain Operations for Fashionable Products

Fashion operations are usually closely related to supply chain operations, quick response, and dynamic pricing. In the scope of fashion supply chain operations, Donohue (2000) examines the optimal supply chain contract for fashion products to achieve supply chain profit maximization. The author reveals that the production cost and lead-time are two crucial factors affecting information updating and contract setting. Nagurney and Yu (2012) examine the equilibrium of competitive fashion supply chains that aim to minimize emissions to achieve sustainability of the fashion supply chain. In addition, several studies explore the quick response and pricing strategies for fashion operations. Aviv et al. (2019) study the optimal pricing strategy (i.e., response pricing and statistic pricing) for fashion products considering the products’ seasonality. The authors find that the response pricing strategy could alleviate the pressure of the inventory backlog. Cachon and Swinney (2011) examine the effect of quick response and design ability on the operation of a fashion firm and find that the quick response mechanism is profitable especially when consumers are strategic.

On the other hand, the fashion literature has paid attention to examining features of luxury fashion, such as high quality and high brand value. For instance, Gao et al. (2017) explore the effects of copycat on incumbent luxury fashion brands. The authors find that high quality is useful to stop the entry of copycats. Mauss (2002) studies the conspicuous use of goods to achieve social categories and status. Chiu et al. (2018) explore the optimal budget allocation on advertising for luxury products. Measuring the risk brought by demand uncertainty, the authors find that the optimal advertising allocation is polarized with the consideration of social influences. This work is mainly related to Mauss (2002) and Chiu et al. (2018) that investigate the significance of consumers’ conspicuous and the optimal advertising strategy. Different from these prior studies, we pay attention to studying the performance

of advertising strategies for luxury fashion operations and try to uncover the optimal strategy for advertising on social media platforms.

2.4.1 Advertising Strategy for Fashionable Products

Advertising strategies have been widely studied over the decades from various perspectives, including the dynamic advertising control (for example, Sethi advertising model (Sethi 1977; Sethi 1983; Huang et al. 2012; Chutani and Sethi 2018), co-op advertising (Huang and Li 2001; Kennedy et al. 2021), advertising signals (Feng and Xie 2012; Chen and Liu 2021; Liu et al. 2021), advertising effects (Mahajan and Muller 1986; Kuksov et al. 2013; Long et al. 2022), etc. This work mainly relates to those analytical studies that examine the advertising effects in online retailing. For example, considering information technology (IT), Liu et al. (2012) explore the effects of “IT capacity” constraints, such as the information traffic delay, on duopolistic retailers advertising strategies. The authors uncover that the advertising may not increase consumers’ purchasing when e-tailers encounter IT constraints and consumers' tolerance of information delay is lower. Hu et al. (2016) focus on the pricing model of advertising and examine the performances of “cost per click” and “cost per action” contracts between advertisers and publishers. The authors find that the performances of these two contracts are affected by the advertiser’s risk aversion. Besides, customized advertising is one key aspect of online advertising. Customized advertising refers to the strategy that firms post tailored content to each group of consumers (Iyer et al. 2005; Gal-Or and Gal-Or 2005). In the early years, customized advertising has been adopted in the competitive market to improve advertising effectiveness and alleviate price competition (Gal-Or and Gal-Or 2005; Iyer et al. 2005;). In an empirical study, Tucker (2013) experimentally proves that users’ privacy becomes important for the implementation of personalized advertisements. The author finds that it is effective to increase the performance of personalized advertisement (i.e., click rate) by enhancing users’ control for privacy. Rafieian and Yoganarasimhan (2020) experimentally identify that the customized advertisements network can achieve profit-maximization by preserving users’ privacy.

Moreover, this work is relevant to controversial advertising (e.g., negative publicity, brand image), especially for examining its effect on firms’ operations. In the literature, Berger et al. (2010) conduct

three empirical studies to explore the possible positive effect of negative publicity. Specifically, the authors find that it is beneficial for firms to embrace the negative publicity as it could increase product sales through the enhancement of consumers' awareness. Similarly, Chatterjee and Zhou (2020) analytically find that consumers' disliking of sponsored content advertisements would be better for advertisers. This work is in line with but different from the prior literature. Similar to studies such as Hu et al. (2016) and Chiu et al. (2018), this work theoretically explores the optimal advertising strategy leveraging the cost. Different from them, we focus on analytically studying the values of customized advertising (Iyer et al. 2005) and negative advertising (Chatterjee and Zhou 2020) together for luxury fashion brands (LFBs). We specifically capture the important effect of negative advertising and examine how the LFB should make the optimal advertising strategy between the customized advertising and non-customized advertising.

2.4.2 Consumer Behaviors for Luxury Fashion Products

Conspicuous consumption is one of the most important aspects of luxury fashion consumption (Veblen 1899; Ko et al. 2019). It refers to the behavior that consumers purchase luxury products aiming to gain a higher social status in the “economical prestige” (Mauss 2002). From this perspective, several analytical studies explore the effects of conspicuous consumption on operations of luxury fashion. For instance, Hartl et al. (2003) analytically study consumers' conspicuous behavior by observing product sales when adopting different pricing strategies. The authors prove that owning the product becomes a status symbol when the product is sold at a higher price at the beginning of the selling period and then declines. Kuksov and Wang (2013) extend the research problem of Hartl et al. (2003) into a competitive situation. The authors find that it is profitable for the fashion company to set a relatively lower price to attract the low type consumers who would like to be recognized to have a higher social status. Furthermore, Li (2019) examines the strategy of product line extensions for a firm that sells “status products”. The author finds that the consumer's preference for status would encourage the firm to extend the product lines, such as increasing the variety of product qualities. Recently, Lee et al. (2021) incorporate the return policy into the exploration of conspicuous consumption. Specifically, the authors find that with the effects of consumers' snobbish and strategic behavior, it is useful for the

firm to overcome challenges brought by consumers' conspicuous behaviors with measures such as using the return policy and extending product lines.

In addition, Amaldoss and Jain (2015) and Lee et al. (2021) propose that conspicuous consumption not only affects the operations strategies of firms but also reflects the social relationships between high-end and low-end consumers. Specifically, it is attractive for low-end consumers to follow the behavior of high-end consumers, while high-end consumers value the exclusivity of products. In this work, we capture this type of social relationship between the fashion leader and fashion follower in our analytical model. However, this work is different from the previous literature in two aspects. First, we particularly explore the significance of social influences on the advertising strategy of luxury fashion brands. Second, we examine the effects of social influences for social media platform (SMP) advertising in which customized advertising is allowed.

2.5 Summary

In this chapter, the literature related to multi-channel operations, platform operations, e-commerce supply chain management, and supply chain operations for fashionable products have been reviewed. It is found that there are plenty of works studying the mentioned research directions. However, the detailed mechanism that can help multi-channel achieve coordination considering the implementation platform operations is crucial, while still under-explored. Compared with the prior literature, several research gaps are identified as follows.

First, from the perspective of multi-channel operation, most of the existing papers study multi-channel operations focusing on offline-to-online (O2O) coordination. That is, studies capture factors related to physical or virtual sales to explore the operation strategy. However, in practice, all types of online channels exist and they are widely implemented by the retailer simultaneously. This work considers the pure online multi-channel operations, such as the dual channel mode including the direct website channel and third-party platform. Based on this setting, this thesis explores the optimal pricing and channel structure strategy under the pure multi-channel operation circumstance.

Second, several previous studies examine the impacts of channel interactions from the perspective of online-to-offline (O2O) exploring the consumer behavior, inventory strategy, etc. For example, buy-

online-and-pick-up-store (BOPS) and buy-online-and-return-to-store (BORS) are studied in the literature. However, there is limited literature paying attention to exploring the cross-channel effects among online channels. For pure online multi-channel operations, the features of the operation that may affect the decisions are different from O2O, such as demand transfer and overflow. This work reveals the impacts of cross-channel influences on the optimal channel selection and coordination, as well as the optimal pricing and quantity strategy, which can help fill gaps in this direction.

Third, platforms can be basically categorized into (pure) product selling (PS) platforms and service platforms according to the functions they serve. Specifically, PS platforms, such as Amazon.com, function as a marketplace where products can be exchanged among several parties, including brands and consumers. Conversely, service platforms focus on providing services for users, rather than selling products. Reviewing prior literature, it is observed that literature related to the operation of product selling platforms always ignores the impacts of cross-channel influences, which is considered in this work. In addition, service platforms, such as social media platforms, play an important part in the e-commerce era, especially with the adoption of disruptive technologies (e.g., big data). However, limited research studies the impacts of service platforms in e-commerce operation, which is explored in this work.

Chapter 3 Cross-Channel Influences in Online Supply Chains⁷⁸

3.1 Problem Statement

3.1.1 Research Background

Mobile devices (including cell phones, iPads, etc.) are playing a dominating role in electronic commerce. Statistics have shown that in the US, 95% of Americans have a mobile phone and more than 75% of them are using smartphones⁹. Statistica reports that 53% of global online traffic actually came from mobile devices. A natural question arises, what should electronic retailers (e-tailers) make use of this market scenario to enhance their operations?

Recent industrial data released by Google highlights the fact that “mobile is the future of retail”¹⁰ as the majority of consumers nowadays would check and use mobile apps for all kinds of shopping. Smart phones are a necessity for consumers in developed markets like the US and even in developed cities of emerging economies like China. In the real world, nowadays, a lot of companies, such as fashion brands, have developed their own mobile apps. The features of these mobile apps vary as different fashion brands have different preferences and philosophies with respect to the use of mobile apps¹¹. For example, some luxury fashion brands (e.g., Chanel and Louis Vuitton) mainly focus on promoting their brand images and creating funs via mobile apps; selling products is of secondary importance and they create a sharp link to the official website as the main sales channel. On the other hand, fast fashion brands employ the mobile apps channel as well as the official website channel (e.g., H&M and P&B) to sell their products¹². No matter which model has been employed, there is no doubt that owing to the popularity of mobile devices, mobile commerce, which refers to the business operations supported mainly by mobile devices (such as “selling via apps”), becomes a critical area for business operations.

⁷ A part of this chapter is presented in “Choi, T.M., Siqin, T., Wen, X, Chung, S.H. (2022). Cross-channel influences in mobile-app-website e-commerce newsvendor supply chains. Under review.

⁸ Abbreviations and notation used are only valid for this chapter.

⁹ <https://www.readycloud.com/info/retailers-dont-ignore-these-mobile-commerce-statistics-for-2019> (accessed: 25 July 2021).

¹⁰ <https://www.smartinsights.com/mobile-marketing/app-marketing/fashion-apps-major-sales-opportunity-fashion-brands/> (accessed 14 July 2021)

¹¹ <https://www.mobilemarketer.com/ex/mobilemarketer/cms/opinion/columns/12763.html> (accessed 14 July 2021)

¹² The detailed descriptions of mobile apps for Chanel, Louis Vuitton, H&M, and P&B in App Store are provided in Appendix I.

When we consider an e-tailer which sells through both the website (WS) channel and the mobile app (MA) channel, the total sales quantity may increase or decrease. If the presence of the MA channel helps increase the demand of the WS channel or vice versa, we say that there is a *channel reinforcement effect*; on the contrary, if the presence of the MA channel reduces the demand of the WS channel or vice versa, it is called the *channel cannibalization effect*. Table 3.1 shows the real-world scenario and information systems design in which each effect exists.

Moreover, with the development of information technologies, fashion brands nowadays are able to invest in forecast-enhancement technology (FET) to help reduce demand uncertainty, which is especially valuable for the retailers operating with multiple channels. The FET investment can be specifically visualized as the investment in information technology such as “demand planning module (DPM)”, which is commonly present in most commercial enterprise solutions such as SAP. For the fashion industry, SAP has its enterprise systems solution to support e-commerce supply chain operations¹³. The DPM is a part of its SAP-APO (Advanced Planning and Optimization) system (see Figure 3.1)¹⁴. The FET investment is becoming increasingly popular in the fashion industry.

In the operations management literature, prior research related to mobile commerce operations has focused mainly on consumer concerns on privacy (Degurmenci 2019), security (Balapour et al. 2020; Wu et al. 2020), and pricing problems for mobile channel in the multi-channel context (Amrouche et al. 2020; Choi 2020). Relatively few studies focus on inventory management considering the mobile sales channel interacting with the traditional website channel, as well as the effect of FET investment. This work aims to bridge this research gap.

Table 3.1. Examples of different cross-channel influences.

Cross-channel influence	Positive influence	Negative influence
Mobile app to website (M2W)	<p>Effect: Channel reinforcement</p> <p>Scenario: Despite allowing the consumers to buy, the mobile app channel is not mainly for selling products. But it helps promote</p>	<p>Effect: Channel cannibalization</p> <p>Scenario: The mobile app and website channels are both mainly for selling products.</p>

¹³ <https://www.sap.com/industries/fashion-apparel.html> (accessed 14 June 2021).

¹⁴ <https://www.sap.com/products/advanced-planning-optimization.html> (accessed 14 June 2021).

products and establish brand loyalty. Consumers who like the mobile app are enticed to buy more.

Information systems design: The selling function is obvious in each channel.

Information systems design: The mobile app is not designed mainly for selling, and there is a clear link in the mobile app to let consumers buy from the official selling website.

Website to mobile app (W2M)

Effect: Channel reinforcement

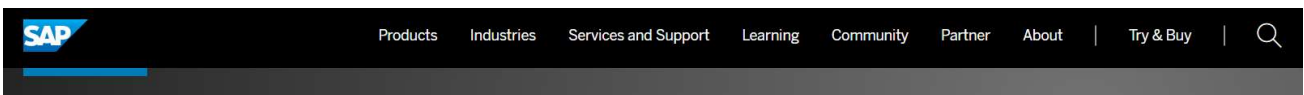
Effect: Channel cannibalization

Scenario: Despite allowing the consumers to buy, the website channel is not mainly for selling products. But it helps promote products and establish brand loyalty. Consumers who like the website are enticed to buy more.

Scenario: The mobile app and website channels are both mainly for selling products.

Information systems design: The selling function is obvious in each channel.

Information systems design: The website is not designed mainly for selling, and there is a strong link to the mobile channel to encourage consumers to buy from the mobile app.



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Figure 3.1. The “SAP Advanced Planning and Optimization” system (with demand planning module).

To be specific, in this study, we consider a dual channel (i.e., mobile app sales channel and website sales channel) e-commerce supply chain consisting of an online retailer (i.e., e-tailer) and a manufacturer. Facing the cross-channel influences discussed above, the e-tailer's inventory management requires careful planning (Wen et al., 2019; Wen and Siqin, 2020). In particular, the e-tailer can adopt risk pooling (by aggregating the demands from MA and WS channels together). Besides, it can invest in forecast-enhancement technology (FET), which helps reduce demand uncertainty, to improve inventory management. However, how specifically the cross-channel influences affect inventory management and e-commerce supply chain performance, and how the e-tailer shall determine the optimal FET investment levels are largely unknown. In addition, how the supply chain structure (e.g., centralized or decentralized) affects the e-tailer's optimal decisions and supply chain members' profits, whether the e-tailer should delink or strengthen channel influences, and how the timely blockchain technology may be applied to enhance the FET investment deserve deeper explorations.

3.1.2 Research Questions and Major Findings

Motivated by the popularity of mobile devices and the emergence of e-commerce as the main business operations nowadays, we build analytical models to address the following core research questions:

1. In the dual channel newsvendor e-commerce supply chain system with both the WS and MA channels, what is the optimal inventory policy in the presence of risk pooling and FET? How would the magnitudes of cross-channel influences affect the optimal inventory decisions and the optimal expected profits of the e-tailer and e-commerce supply chain?
2. How to coordinate the dual channel e-commerce supply chain system using supply chain contracts under Nash bargaining? How would the magnitudes of cross-channel influences affect the setting of coordination contracts?
3. Exploring the cross-channel influences, when would it be optimal to delink the channels or strengthen the cross-channel influence under the decentralized and centralized cases? If blockchain technology can be employed to improve the efficiency of FET investment, when will it be optimal to implement blockchain? Does it affect the “delink” or “strengthen” decision?

As we will demonstrate in the subsequent sub-chapters, addressing the above research questions uncovers many important findings. We derive the optimal ordering decision and uncover that the e-tailer's optimal ordering quantity and the corresponding optimal expected profit are affected by the magnitude of cross-channel influences. Owing to the features of the MA-WS dual channel, we have four models (Models RR, RC, CR and CC) capturing the directional channel reinforcement effect and channel cannibalization effect. However, we innovatively find that the optimal FET investment level is independent of the cross-channel influence. Then, we show that the dual channel MA-WS e-commerce supply chain system under Nash bargaining can be coordinated by various widely adopted supply chain contracts. For the coordinated (or centralized) e-commerce supply chain system, impacts brought by a larger magnitude of cross-channel influence on the coordination contract parameters settings depend on the specific contract type. Moreover, for the coordinated (or centralized) e-commerce supply chain system, impacts brought by a larger magnitude of cross-channel influence on the centralized e-commerce supply chain's optimal ordering quantity and the corresponding optimal expected profit follow the same pattern as in the e-tailer's case under the decentralized uncoordinated supply chain setting. From these results, we reveal that for the coordinated e-commerce supply chain system, whether it is optimal to delink channels or strengthen cross-channel influences follows the results in Table 3.1. We highlight a few insights: First, the optimal "delink" or "strengthen" decisions relate to the specific directional cross-channel influence. For instance, under Model RC, it is always wise to delink the M2W (mobile app to website) channel while it is wise to strengthen the W2M (website to mobile app) channel if the M2W channel influence is sufficiently small. Second, whether to choose delink or strength depends on models. The corresponding pattern follows whether increasing or decreasing magnitude of a cross-channel influence will lead to a higher expected profit for the e-commerce supply chain system. Since the e-commerce supply chain is coordinated under Nash bargaining model, a higher e-commerce supply chain expected profit directly implies a higher profit for each channel member. Third, for the models involving "C", i.e., the channel cannibalization effect (cf.: Model RC, Model CR, and Model CC), the optimal decision on "delink" and "strengthen" a particular cross-channel influence may depend on the size of the cross-channel influence. Finally, we consider the probable use of blockchain to improve the effectiveness of FET investment. We uncover

that whether the e-tailer should consider implementing blockchain highly depends on the per period fixed blockchain operations cost (for both the decentralized uncoordinated, and centralized/coordinated e-commerce supply chains). It is interesting to observe that the use of blockchain or not does not affect the optimal decisions on “delink” channels or “strengthen” cross-channel influences. This is an important result as it implies that the e-tailer can do two enhancements, implementing blockchain (to improve demand forecasting) and redesigning the website (with “delink and strengthen”), without worrying about one another as they are independent. Furthermore, if it is optimal to use blockchain, when we check the impacts brought by changes of the cross-channel influences, we will find that the same pattern as in the cases without blockchain appears.

3.2 Basic Models

This work focuses on e-commerce operations. We explore an e-commerce supply chain system that produces and sells a newsvendor type¹⁵ of fashionable product by the manufacturer and the e-tailer, respectively. The e-tailer has established a classic website (WS) channel and a mobile-app (MA) channel to sell a forthcoming new product. The abbreviations used is summarized in Table 3.2. The e-tailer needs to decide the ordering quantity Q from the manufacturer. The MA-WS dual channel operations are depicted in Figure 3.2.

Table 3.5. Definitions of abbreviation.

Abbreviation	Meaning
MA	Mobile app
WS	Website
FET	Forecast enhancement technology
CR	Channel reinforcement
CC	Channel cannibalization
M2W	MA-to-WS channel
W2M	WS-to-MA channel
TT	Two-part-tariff
PS	Profit sharing
MS	Markdown sponsor

¹⁵ We consider the case in which demand of the fashionable product is uncertain, and the e-tailer should decide the optimal ordering quantity. Therefore, we make use of the newsvendor model.

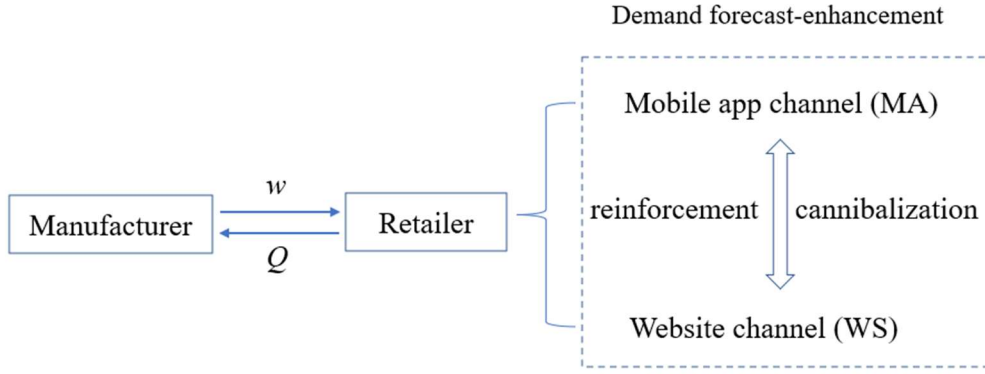


Figure 3.2. MA-WS dual channel operations.

The expected market potentials for the WS and MA channels are given by a and α , respectively. We summarized notation used in Table 3.3. Denote the expected market demands for the WS and MA channels respectively by d_{WS} and d_{MA} . Since the two channels may influence one another, we model them as follows: $d_{MA} = a + \gamma d_{WS}$ and $d_{WS} = \alpha + \lambda d_{MA}$, where $-1 < \gamma < 1$ and $-1 < \lambda < 1$ represent the cross-channel influences (Huang et al. 2013). Note that when γ and λ are positive, the two channels support one another and the effect is called “channel reinforcement (CR) effect”. When γ and λ are negative, the two channels fight against one another and the effect is called “channel cannibalization (CC) effect”. When γ and λ take different signs, then both CC and CR effects are present. When γ and λ are zero, the MA and WS channels are independent of one another. To reflect the magnitude of the CC or CR effect (i.e., the cross-channel influence), we define the following: $|\gamma| = g$ and $|\lambda| = l$. Table 3.4 shows the unique features that the model captures for the WS-MA dual channel e-commerce supply chain, which clearly differentiate this work from the other dual channel (e.g., online-offline) studies.

Table 3.12. Definitions of parameters of basic model.

Parameter	Meaning
a	The expected market potential for WS channel, $a \geq 0$.
α	The expected market potential for MA channel, $\alpha \geq 0$.
Q	The ordering quantity.
γ	The MA-to-WS channel influence, $-1 < \gamma < 1$.
λ	The WS-to-MA channel influence, $-1 < \lambda < 1$.
σ_{MA}^2	The variance of demand for channel MA.
σ_{WS}^2	The variance of demand for channel WS.

ρ	The correlation coefficient between demands of channel MA and WS.
c	The unit production cost, $c \geq 0$.
w	The unit wholesale price, $w > 0$.
v	The unit net salvage value, $v > 0$.

Table 3.4. Unique features that the model captures for the WS-MA dual channel operations.

	WS-MA Dual Channel Operations	Online-offline Channel Operations
Effects	Both channel reinforcement and channel cannibalization effects are commonly present	The channel cannibalization effect is dominating (Cai et al. 2009)
Inventory management	Both channels are online and inventory aggregation (i.e., risk pooling) becomes critical	The online and offline channels may have different inventory planning as offline channel has its own physical store with inventory
Key strategic actions	Designs of website and mobile apps are critical	For online-offline operations, integration is critical and the specific arrangement, such as “buy online pickup offline”, becomes crucial (Gao and Su, 2017)

From $d_{MA} = a + \gamma d_{WS}$ and $d_{WS} = \alpha + \lambda d_{MA}$, it is easy to find that: $d_{MA} = \frac{a + \alpha\gamma}{1 - \lambda\gamma}$ and $d_{WS} = \frac{\alpha + a\gamma}{1 - \lambda\gamma}$.

We consider that the e-tailer can adopt the risk pooling strategy. We thus model the random demands of channels MA and WS to be normally distributed with variances σ_{MA}^2 and σ_{WS}^2 :

$x_{MA} \sim Normal\left(\frac{a + \alpha\gamma}{1 - \lambda\gamma}, \sigma_{MA}^2\right)$ and $x_{WS} \sim Normal\left(\frac{\alpha + a\gamma}{1 - \lambda\gamma}, \sigma_{WS}^2\right)$, and the correlation coefficient between

x_{MA} and x_{WS} is ρ . To avoid the trivial cases, we consider the ρ is not too small, e.g., $\rho > -\frac{\sigma_{MA}}{\sigma_{WS}}$.

Denote $S = \sqrt{\sigma_{MA}^2 + \sigma_{WS}^2 + 2\rho\sigma_{MA}\sigma_{WS}}$. Note that we explore the case with the normally distributed demand because it is commonly used in the related literature (Iyer and Bergen 1997; Choi et al. 2018), and we also try to highlight the forecast enhancement effect by reducing the demand variance. The use of normal distribution will make the points very clear.

For the product, we model it by using the standard newsvendor model in which the unit retail price is p . In the basic model, we consider the manufacturer transacts with the e-tailer using the pure wholesale pricing contract. The cost for producing unit product is c and the wholesale price of unit

product is w . The product is sold by the e-tailer for a single selling season. The unit net salvage value of product leftover is v . Since we employ the normal distribution, we define the following notation for the standardized normal distribution: $\phi(\cdot)$, $\Phi(\cdot)$ and $\Psi(z) = \int_z^\infty (x-z)\phi(x)dx$ are the standardized normal probability density function, standardized normal cumulative distribution function, and standardized normal right linear loss function, respectively. We further represent the inverse function of $\Phi(\cdot)$ by $\Phi^{-1}(\cdot)$.

In order to improve the operational performance, the e-tailer can reduce σ_{MA}^2 and σ_{WS}^2 by investing in a *forecast enhancement technology* (FET) at a cost. This FET technology can be viewed as the demand planning module in most enterprise systems. Investing in it means enhancing its functionality and effectiveness by having better technologies or intelligent algorithms. We represent the level of FET adoption by θ and the corresponding FET investment by $K(\theta)$. Following the literature, we model $K(\theta)$ as a convex and strictly increasing function with which $\partial K(\theta)/\partial\theta > 0$ and $\partial^2 K(\theta)/\partial\theta^2 \geq 0$. With θ , demand standard deviations of both channels MA and WS are reduced by a factor of $\varepsilon(\theta)$, where $\varepsilon(\theta)$ is decreasing in θ . Denote $B_R = (p-v)\phi\left(\Phi^{-1}\left(\frac{p-w}{p-v}\right)\right)$.

For a given θ , we can easily find the e-tailer's expected profit as follows.

$$\Pi_R(Q|\theta) = (p-v) \left[\left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right) - \varepsilon(\theta)S \left[\Psi \left(\frac{Q - \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right)}{\varepsilon(\theta)S} \right) \right] \right] - (w-v)Q - K(\theta).$$

In the following, we show the optimal ordering quantity Q^* and the corresponding optimal expected profit value for given θ :

$$Q_R^* |_\theta = \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right) + \varepsilon(\theta)S\Phi^{-1}\left(\frac{p-w}{p-v}\right), \text{ and} \quad (3.1)$$

$$\Pi_R^* |_\theta = (p-w) \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right) - K(\theta) - \varepsilon(\theta)B_R S. \quad (3.2)$$

Maximizing (3.2) with respect to θ yields the optimal FET adoption level, which we denote by $\theta_R^* = \arg \max_{\theta} \Pi_R^* |_\theta = \arg(\partial \Pi_R^* |_\theta / \partial \theta = 0)$. Note that as our results do not depend on the exact form of θ_R^* ,

we need not confine ourselves to any specific form of $\varepsilon(\theta)$ and $K(\theta)$. θ_R^* is also unrelated to γ and λ . Table 3.5 shows some examples of θ_R^* when $\varepsilon(\theta)$ and $K(\theta)$ take some specific functional forms.

Table 3.5. Examples of θ_R^* with some specific $\varepsilon(\theta)$ and $K(\theta)$.

EXAMPLES	SPECIFIC FUNCTIONS	θ_R^*
1	$K(\theta) = \beta\theta^2 / 2,$ $\varepsilon(\theta) = 1 - \theta$, where $\beta > 0$	$\frac{SB_R}{\beta}$
2	$K(\theta) = h\theta,$ $\varepsilon(\theta) = e^{-\eta\theta}$, where $h > 0$ and $\eta > 0$	$\frac{1}{\eta} \ln\left(\frac{\eta SB_R}{h}\right)$

From the above results, we have the following findings: With the optimal FET investment level θ_R^* , the optimal ordering quantity and the optimal e-tailer's expected profit are given below:

$$Q_R^* = \left(\frac{a + \alpha + a\lambda + \alpha\gamma}{1 - \lambda\gamma} \right) + \varepsilon(\theta_R^*) S \Phi^{-1}\left(\frac{p - w}{p - v} \right), \text{ and} \quad (3.3)$$

$$\Pi_R^* = (p - w) \left(\frac{a + \alpha + a\lambda + \alpha\gamma}{1 - \lambda\gamma} \right) - K(\theta_R^*) - \varepsilon(\theta_R^*) B_R S. \quad (3.4)$$

3.3 Impacts of Cross-channel Influences

In order to study the effects of cross-channel influences on the optimal inventory decisions and supply chain members' profits, we consider four cases in the four models as listed in Table 3.6. The meanings of these models are also included.

Table 3.6. Definitions of the four models under investigation.

MODELS	γ	λ	MEANINGS
Model RR	Positive	Positive	The WS and MA channels reinforce and support one another in terms of increasing demands
Model CR	Negative	Positive	The presence of WS channel reduces the MA channel's demand. The MA channel increases the WS channel's demand
Model RC	Positive	Negative	The presence of WS channel increases the MA channel's demand. The MA channel decreases the WS channel's demand
Model CC	Negative	Negative	The WS and MA channels cannibalize one another in terms of reducing demands

To enhance presentation and analysis, define: $\bar{l} = \frac{a - g(a + \alpha + \alpha g)}{2ag}$ and $\bar{g} = \frac{\alpha - l(\alpha + a(1+l))}{2\alpha l}$.

We can construct Table 3.7. Note that as defined in Chapter 3.2: (i) $l = |\lambda|$ represents the magnitude of MA-to-WS (M2W) channel influence, and (ii) $g = |\gamma|$ denotes the magnitude of WS-to-MA (W2M) channel influence. They are both called the cross-channel influences.

Table 3.7. Effects brought by an increased magnitude of cross-channel influence on $Z_R \in \{Q_R^*, \Pi_R^*\}$ under different models in the basic model (decentralized).

		MODELS			
		MODEL RR	MODEL RC	MODEL CR	MODEL CC
$l \uparrow$ (M2W channel influence increases)			$Z_R \downarrow$	$Z_R \begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix} \text{ iff } g \begin{pmatrix} < \\ = \\ > \end{pmatrix} \frac{a}{\alpha}$	$Z_R \begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix} \text{ iff } g \begin{pmatrix} > \\ = \\ < \end{pmatrix} \frac{a}{\alpha}$
	$Z_R \uparrow$				
$g \uparrow$ (W2M channel influence increases)			$Z_R \begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix} \text{ iff } l \begin{pmatrix} < \\ = \\ > \end{pmatrix} \frac{\alpha}{a}$	$Z_R \downarrow$	$Z_R \begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix} \text{ iff } l \begin{pmatrix} > \\ = \\ < \end{pmatrix} \frac{\alpha}{a}$

From Table 3.7, we can see that there are four different models (each carries the respective physical meaning) and several interesting findings can be obtained as discussed below.

First, when the “channel reinforcement effect” exists (i.e., Model RR, Model RC, and Mode CR), depending on models, an increasing magnitude of the channel reinforcement effect brings different effects. Model RR, in which both the MA and WS channels reinforce one another, is the simplest one in which a larger M2W or W2M channel influence will lead to a larger optimal ordering quantity by the e-tailer, as well as a higher optimal profit of the e-tailer. However, under Model RC and Model CR, the increasing magnitude of the reinforcement effect (i.e., W2M of Model RC and M2W of Model CR) can lead to the larger or smaller optimal ordering quantity and optimal profit, which depends on the size of the other channel influence (i.e., M2W and W2M for Model RC and Model CR,

respectively). If the other channel influence is substantially large (small), increasing it further increases (reduces) the retailer's optimal ordering quantity and optimal expected profit.

Second, for Model RC and Model CR, and Model CC in which the "channel cannibalization effect" is present, impacts brought by an increasing magnitude of channel cannibalization effect are different depending on the Model. For hybrid models when both the channel cannibalization and reinforcement effects are present, it is straightforward to observe that the increase in channel cannibalization effect leads to a smaller optimal ordering quantity and profit. It is because the enhanced channel cannibalization effects (i.e., M2W (W2M) channel influence for Model RC (CR)), results in the loss of demand in the MS or MA channel, which eventually leads to the smaller optimal ordering quantity and optimal profit. By contrast, under Model CC, in which only the channel cannibalization effect is present for two directional channel influences, the impacts of one channel influence depend on the size of the other channel influence. For example, only when the magnitude of W2M channel influence (i.e., g) is relatively larger (resp. smaller), can the increase of M2W channel influence (i.e., l) leads to the increase (resp. decrease) of the e-tailer's optimal ordering quantity and optimal profit.

Third, as discussed, the optimal FET investment level is not affected by the magnitude of cross-channel influences. This means that the cross-channel influences are important in affecting the inherent ordering decisions but do not affect the optimal investment for forecasting improvement. As such, e-tailers consider the optimal investment for improving demand forecast, the magnitudes of cross-channel influences are unimportant.

Proposition 3.1. *Under the basic model, impacts brought by a larger magnitude of cross-channel influences on the e-tailer's optimal ordering quantity and the corresponding optimal expected profit depend on the specific model (see Table 3.6 for the model definitions). However, the optimal FET investment level θ_R^* is independent of the cross-channel influences.*

The cross-channel influence plays a role if both the mobile app and website channel are used. Proposition 3.1 highlights how the e-tailer should make ordering decisions and its expected profit depend on the specific cross-channel influences (i.e., W2M, M2W, channel reinforcement, channel cannibalization). More specifically, the e-tailer can strategically create the channel reinforcement and channel cannibalization effects to improve profitability. For example, some luxury fashion brands, like

Chanel, develop their mobile apps for the promotion purpose, in which there is a sharp link to the official website for product selling. In this case, the M2W channel reinforcement effect exists. This channel strategy may be profitable for the Chanel when Model RR and Model CR can be achieved. As observed, it is valuable for the e-tailer to take the type of cross-channel influences into consideration when making ordering decisions. In contrast, the optimal FET investment level is irrelevant to the cross-channel influences as the technology investment is used to enhance demand forecasting.

3.4 Impacts of Demand Uncertainties and Market Potentials

To study the impacts of the demand uncertainty, we adopt the form of $\varepsilon(\theta)$ and $K(\theta)$ shown as Example 1 in Table 3.5. Accordingly, the optimal FET adoption level θ_R^* equals $\frac{SB_R}{\beta}$. In this part, we deeply examine the impacts of demand uncertainty and market potentials on the optimal ordering quantity, FET investment level, and expected profit.

Table 3.8. Effects brought by the increased demand uncertainty¹⁶.

	MODELS		
	Q_R^*	θ_R^*	Π_R^*
$\sigma_{MA} \uparrow / \sigma_{WS} \uparrow$ (Demand uncertainty of channel MA/WS increases)	$\begin{pmatrix} \downarrow \\ \uparrow \end{pmatrix}$ iff $S \begin{pmatrix} > \\ < \end{pmatrix} \frac{\beta}{B_R}$	\uparrow	$\begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix}$ iff $S \begin{pmatrix} > \\ < \end{pmatrix} \frac{\beta}{B_R}$

Proposition 3.2 *Impacts brought by demand uncertainty on the e-tailer's optimal ordering quantity and the corresponding optimal expected profit closely related to the demand standard deviation of the WS-MA dual channel system (i.e., S). Besides, the optimal FET investment level θ_R^* increases in demand uncertainty.*

By constructing sensitivity analysis of the optimal quantity, FET investment level, and optimal

¹⁶ We consider the safety stock $\Phi^{-1}\left(\frac{p-w}{p-v}\right)$ is positive, which means the e-tailer prepares extra inventory to mitigate the risk of random demand (Porteus 2002).

profit with respect to demand uncertainties σ_{MA} and σ_{WS} shown in Table 3.8, Proposition 3.2 provides how the e-tailer can decide optimal decisions facing the volatile market when aggregating the two channels. To be specific, when the mobile app and website channels are both used, the demand volatility for the aggregated dual channel system is captured by S . A larger (smaller) S implies demand volatility of this dual channel system is high (low). Our analytical results show that, with the increase of demand uncertainty of one channel, it is optimal for the e-tailer to order less if the demand volatility of this dual channel system is higher than a threshold. The reason behind can be explained as follows. When the demand of one channel becomes more uncertain, the optimal ordering decision of the system (recall $Q_R^* = \left(\frac{a + \alpha + a\lambda + \alpha\gamma}{1 - \lambda\gamma} \right) + \varepsilon(\theta_R^*)S\Phi^{-1}\left(\frac{p-w}{p-v}\right)$) is affected by two opposite effects.

First, the increase in demand forecasting investment would help reduce the ordering quantity. Second, the growth in S would lead to a higher ordering quantity. When S is beyond a threshold (i.e., $S > \frac{\beta}{2B_R}$), the reduction effect led by the higher demand forecasting investment exceeds the increase effect led by the higher S , thus causing a decline in the overall ordering quantity. In this situation, it is profitable for the e-tailer to reduce the optimal ordering quantity to avoid loss from the inventory backlog. On the other hand, it is rational that the e-tailer should improve the optimal FET investment level to improve demand forecasting ability with the increased demand uncertainties.

Proposition 3.3 *The e-tailer's optimal ordering quantity and the corresponding optimal expected profit are increased with market potentials. However, the optimal FET investment level θ_R^* is independent of the market potentials.*

Proposition 3.3 presents the impacts of market potentials on the e-tailer's optimal decisions and expected profit. Facing larger market potentials from two channels, it is optimal for the e-tailer to order more products to increase sales, which results in a higher expected profit. However, how the e-tailer should make the optimal FET investment level is independent of the market potential, while is affected by the uncertainties as we found in Proposition 3.2.

3.5 Further Analyses

3.5.1 Coordination Contracting and Centralized E-commerce Supply Chain

In Chapters 3.3 and 3.4, we examine the decentralized e-commerce supply chain. Now, in the centralized e-commerce supply chain, for a given θ , the e-commerce supply chain's expected profit is:

$$\Pi_{SC}(Q|\theta) = (p-v) \left[\left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right) - \varepsilon(\theta)S \left[\Psi \left(\frac{Q - \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right)}{\varepsilon(\theta)S} \right) \right] \right] - (c-v)Q - K(\theta).$$

$$\text{Denote } B_{SC} = (p-v)\phi \left[\Phi^{-1} \left(\frac{p-c}{p-v} \right) \right].$$

The optimal product quantity and expected profit of the e-commerce supply chain are given below:

$$Q_{SC}^* |_{\theta} = \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right) + \varepsilon(\theta)S\Phi^{-1} \left(\frac{p-c}{p-v} \right), \text{ and} \quad (3.5)$$

$$\Pi_{SC}^* |_{\theta} = (p-c) \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right) - K(\theta) - \varepsilon(\theta)B_{SC}S. \quad (3.6)$$

Following the approach in deriving (3.3) and (3.4) we can see that $\theta_{SC}^* = \arg \max_{\theta} \Pi_{SC}^* |_{\theta} = \arg(\partial \Pi_{SC}^* |_{\theta} / \partial \theta = 0)$. With the optimal FET investment level θ_{SC}^* , the “unconditional” optimal product quantity and the corresponding optimal e-commerce supply chain's expected profit are given below: $Q_{SC}^* = \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right) + \varepsilon(\theta_{SC}^*)S\Phi^{-1} \left(\frac{p-c}{p-v} \right)$, and

$$\Pi_{SC}^* = (p-c) \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right) - K(\theta_{SC}^*) - \varepsilon(\theta_{SC}^*)B_{SC}S.$$

Chapter 3.3 studies the e-commerce supply chain system with a pure wholesale pricing contract, which cannot coordinate the e-commerce supply chain. In this chapter, we explore whether three commonly seen and useful supply chain contracts can achieve supply chain coordination. To be specific, we consider the two-part-tariff (TT) contract, profit sharing (PS) contract, and markdown sponsor (MS) contract. To establish the optimal contracts, suppose that the manufacturer and the e-tailer have the bargaining powers of $(1-\xi)$ and ξ , respectively. We employ the Nash bargaining

model. Here, we define the standard ‘‘Nash Bargaining Product’’ (NBP) under a contract $i \in (TT, PS, MS)$ by $\Omega_{NBP} = \{\Pi_R^i(Q)\}^\xi \{\Pi_M^i(Q)\}^{1-\xi}$. The solution for the Nash bargaining scenario solves the following optimization problem (Choi et al. 2020; Shi et al. 2020):

$$\text{Max } \Omega_{NBP} = \{\Pi_R^i(Q; \theta)\}^\xi \{\Pi_M^i(Q; \theta)\}^{1-\xi}$$

$$\text{Subject to. } \Pi_R^i(Q; \theta) + \Pi_M^i(Q; \theta) \leq \Pi_{SC}(Q_{SC}^*; \theta_{SC}^*).$$

For the TT contract, the manufacturer controls the unit wholesale price w_{TT} and the side-payment Y_{TT} (from the e-tailer to the manufacturer). For the PS contract, the manufacturer sets the unit wholesale price w_{PS} and requests to receive ‘‘ s_{PS} proportion of the e-tailer’s profit’’ as a profit share. For the MS contract, the manufacturer controls the unit wholesale price w and the unit markdown sponsor m for every unit of unsold product leftover in the e-tailer. Table 3.9 shows how the contract can be set to achieve coordination (see Appendix for the proof).

Table 3.9. Achieving coordination by contracts.

CONTRACTS	CONTRACT SETTINGS
TT	$w_{TT}^* = c,$ $Y_{TT}^* = (1 - \xi)\Pi_{SC}^*.$
PS	$w_{PS}^* = c,$ $s_{PS}^* = (1 - \xi).$
MS	w_{MS}^* and m_{MS}^* are the solutions of the following simultaneous equations: $w_{MS}^* = p - \left(\frac{\xi \Pi_{SC}^* + K(\theta_{SC}^*)}{J - \left(\frac{p-v}{p-c}\right)\varepsilon(\theta_{SC}^*)\phi\left[\Phi^{-1}\left(\frac{p-w}{p-v-m}\right)\right]} \right), \text{ where } J = \left(\frac{a + \alpha + a\lambda + \alpha\gamma}{1 - \lambda\gamma} \right),$ $m_{MS}^* = \frac{(p-v)(w_{MS}^* - c)}{(p-c)}.$

Proposition 3.4. *The dual channel e-commerce supply chain system under Nash bargaining can be coordinated by the TT, PS and MS contracts.*

Note that since the e-tailer and manufacturer negotiate under the Nash bargaining model, the contract setting is governed by their respective bargaining powers and is unique for each contract. For

the TT and PS contracts, the setting relies on supplying at cost and then sharing the total optimal e-commerce supply chain expected profit with respect to the Nash bargaining result (e.g., ξ). Specifically, under the TT and PS contract, when the e-tailer has relatively higher bargaining power, the e-tailer could pay less to the manufacturer, leading to a lower profit for the manufacturer. On the other hand, if the MS contract is used, the contract setting is more complex while it is still feasible. Regarding the effect of bargaining power on supply chain coordination, it is observed that the higher bargaining power of the manufacturer helps increase the wholesale price (thus generating a higher profit). This finding is consistent with the previous literature, such as Gal-Or (2004). In the following, we further explore the impacts of cross-channel influences on the contract parameters for supply chain coordination. The findings are summarized in Table 3.10.

Table 3.10. Effects brought by an increased magnitude of cross-channel influence on contract parameter setting.

Table 3.10a. The TT and PS contracts¹⁷.

	CONTRACTS	
	CONTRACT TT	CONTRACT PS
$l \uparrow$ (M2W channel influence increases)	No effect on supply chain contracting parameters which achieve coordination	No effect on supply chain contracting parameters which achieve coordination
$g \uparrow$ (W2M channel influence increases)		

Table 3.10b. The MS contract ($\Omega_{MS} \in \{w_{MS}^*, m_{MS}^*\}$)¹⁸.

	MODELS			
	MODEL RR	MODEL RC	MODEL CR	MODEL CC
$l \uparrow$ (M2W channel influence increases)		$\Omega^{MS} \uparrow$	$\Omega^{MS} \begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix} \text{ iff } g \begin{pmatrix} > \\ = \\ < \end{pmatrix} \frac{a}{\alpha}$	$\Omega^{MS} \begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix} \text{ iff } g \begin{pmatrix} < \\ = \\ > \end{pmatrix} \frac{a}{\alpha}$
$g \uparrow$ (W2M channel influence increases)	$\Omega^{MS} \downarrow$	$\Omega^{MS} \begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix} \text{ iff } l \begin{pmatrix} > \\ = \\ < \end{pmatrix} \frac{\alpha}{a}$	$\Omega^{MS} \uparrow$	$\Omega^{MS} \begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix} \text{ iff } l \begin{pmatrix} < \\ = \\ > \end{pmatrix} \frac{\alpha}{a}$

¹⁷ We adopt the form of $\mathcal{E}(\theta)$ and $K(\theta)$ as shown in Example 1 of Table 3.5.

¹⁸ Note that Table 3.10 shows one of possible results regarding the sensitive analysis.

Proposition 3.5. *For the coordinated (or centralized) e-commerce supply chain system, impacts brought by a larger magnitude of cross-channel influence on the coordination contract parameters settings depend on the specific contract type. For the TT and PS contracts, there is no effect. For the MS contract, the impacts are as shown in Table 3.10, which also depend on the specific model which appears.*

From Proposition 3.5, we can see that to coordinate the dual channel e-commerce supply chain, the TT and PS contracts are simpler, as the coordination contract parameters are independent of the cross-channel influences. On the other hand, the utilization of MS contract is much more complicated as the contract parameters are affected by the cross-channel influences. The impacts of cross-channel influences further depend on the four possible scenarios. For example, when MA and WS channels reinforce one another (i.e., Model RR), a larger cross channel (W2M and M2W) influence (i.e., more significant channel reinforcement) induces a decrease in the optimal wholesale price and markdown sponsor. However, when the MA and WS channels cannibalize one another (i.e., Model CC), with the increase of cross-channel influence magnitude, the manufacturer should first increase the wholesale price and markdown sponsor; while, when these two channels are seriously cannibalized by each other, the manufacturer is optimal to decrease the wholesale price and markdown sponsor to offset the cannibalization, so as to achieve the coordination of the e-commerce supply chain.

We further check how the cross-channel influences affect the optimal production quantity as well as the optimal expected profit of the centralized e-commerce supply chain. Conducting sensitivity analysis, Table 5.3 summarizes the effects brought by an increased magnitude of cross-channel influence on $Z_{SC} \in \{Q_{SC}^*, \Pi_{SC}^*\}$, which are consistent with the e-tailer's scenario under the decentralized e-commerce supply chain case.

Table 3.11. Effects brought by an increased magnitude of cross-channel influence on $Z_{SC} \in \{Q_{SC}^*, \Pi_{SC}^*\}$ under different models in the centralized (or coordinated) e-commerce supply chain system.

		MODELS			
		MODEL RR	MODEL RC	MODEL CR	MODEL CC
$l \uparrow$ (M2W channel influence increases)			$Z_R \downarrow$	$Z_R \begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix} \text{ iff } g \begin{pmatrix} < \\ = \\ > \end{pmatrix} \frac{a}{\alpha}$	$Z_R \begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix} \text{ iff } g \begin{pmatrix} > \\ = \\ < \end{pmatrix} \frac{a}{\alpha}$
	$Z_R \uparrow$				
$g \uparrow$ (W2M channel influence increases)			$Z_R \begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix} \text{ iff } l \begin{pmatrix} < \\ = \\ > \end{pmatrix} \frac{\alpha}{a}$	$Z_R \downarrow$	$Z_R \begin{pmatrix} \uparrow \\ \downarrow \end{pmatrix} \text{ iff } l \begin{pmatrix} > \\ = \\ < \end{pmatrix} \frac{\alpha}{a}$

We further check how the cross-channel influences affect the optimal production quantity of the e-commerce supply chain as well as the optimal expected profit of the e-commerce supply chain. Proposition 3.6 shows the results which are consistent with the e-tailer's scenario under the decentralized e-commerce supply chain case (P.S.: Proposition 3.1).

Proposition 3.6. *For the coordinated (or centralized) e-commerce supply chain system, impacts brought by a larger magnitude of cross-channel influence on the centralized e-commerce supply chain's optimal ordering quantity and the corresponding optimal expected profit follow the same pattern as in the e-tailer's case (see Proposition 3.1).*

Proposition 3.6 uncovers an important finding. The results in Proposition 3.1 are robust to the e-tailer as well as to the whole dual channel e-commerce supply chain system. That is to say, the e-tailer and e-commerce supply chain should keep their strategy consistent when the supply chain is either decentralized or centralized in response to the changes in the WS-MA cross-channel influences.

3.5.2 Delink Channels or Strengthen Channel Relationships

If the e-tailer can reduce the magnitudes of cross-channel influences (e.g., delink the channels, such as not referring to the website by the mobile app, etc.) or increase them (e.g., establish more connections

and facilitating referral from one channel to the other one), when should the e-tailer make the respective decisions? To answer this question, we have to compare among the four models (Table 3.6).

To be specific, suppose that the e-commerce supply chain is already coordinated (by employing anyone of the three proposed supply chain contracts in Table 3.9). Then, depending on the current model in which the e-commerce supply chain operates with, we have our strategies which follow Table 3.12. The results are summarized in Proposition 3.7.

Proposition 3.7. *For the coordinated e-commerce supply chain system, it is optimal to delink channels or strengthen cross-channel influences following Table 3.12 (P.S.: Delink = weaken the cross-channel influence by removing the respective directional link. Strengthen = strengthen the cross-channel influence by adding or enhancing the respective directional link.)*

Table 3.12. Optimal decisions: To delink or strengthen the respective influence.

		MODELS			
		MODEL RR	MODEL RC	MODEL CR	MODEL CC
M2W channel influence			<i>Delink</i>	<i>Strengthen if $g < \frac{a}{\alpha}$</i>	<i>Strengthen if $g > \frac{a}{\alpha}$</i>
				<i>No action if $g = \frac{a}{\alpha}$</i>	<i>No action if $g = \frac{a}{\alpha}$</i>
				<i>Delink if $g > \frac{a}{\alpha}$</i>	<i>Delink if $g < \frac{a}{\alpha}$</i>
	<i>Strengthen</i>				
W2M channel influence			<i>Strengthen if $l < \frac{\alpha}{a}$</i>	<i>Delink</i>	<i>Strengthen if $l > \frac{\alpha}{a}$</i>
			<i>No action if $l = \frac{\alpha}{a}$</i>		<i>No action if $l = \frac{\alpha}{a}$</i>
			<i>Delink if $l > \frac{\alpha}{a}$</i>		<i>Delink if $l < \frac{\alpha}{a}$</i>

From Table 3.12, similar to the results in Table 3.11, we also have four different models and various interesting results are found.

First, the optimal “delink” or “strengthen” decisions relate to the specific cross-channel influence which has “direction”. For example, under Model RC, it is always beneficial to delink the M2W (mobile app to website) channel while it is beneficial to strengthen the W2M (website to mobile app) channel if the M2W channel influence is sufficiently small (i.e., $l < (\alpha / a)$).

Second, whether to choose delink or strengthen depends on models. The corresponding pattern follows whether increasing or decreasing the magnitude of a cross-channel influence will lead to a higher expected profit for the e-commerce supply chain system. Since the e-commerce supply chain is coordinated under Nash bargaining model, a higher e-commerce supply chain expected profit directly implies a higher profit for each channel member.

Third, for Model RC, Model CR, and Model CC in which the “channel cannibalization effect” is present, the optimal decision on delink and strengthen a particular cross-channel influence may depend on the size of the cross-channel influence. For example, under Model CR, whether it is optimal to delink or strengthen the M2W channel influence depends on the size of the W2M channel influence. If the W2M channel influence is sufficiently small (resp. big), it will be optimal to choose “strengthen” (resp. “delink”).

Forth, it is important to note that “delink” or “strengthen” would involve some design of the mobile apps and websites (e.g., building or removing referrals, links, etc.). While the respective designs mainly incur some fixed costs, we treat them as sunk costs and do not include them into the operations cost because in real life, these sunk costs would be very small compared to the transactions concluded from e-tailing sales.

Finally, for each specific model, we analyze the impacts of market potential on the size of the cross-channel influence, which eventually affects the decision of “delink” and “strengthen”.

Corollary 3.1. *Under Model RC, the supply chain is more likely to strengthen channels when the relative market potential A is increasing, and vice versa; Under Model CR, the increase of A leads to the supply chain is more like to delink channel, and vice versa; Under Model CC, whether the supply chain is more likely to strengthen or delink channel influences with respect to A depends on the specific effect of channel influences, where $A = \frac{\alpha}{a}$.*

Corollary 3.1 uncovers that the “delink” and “strengthen” decisions are affected by the ratio of market potentials between the two channels and the specific model. We define $A = \alpha/a$ as the relative market potential (i.e., the ratio of the market potentials of the MA channel to the WS channel). A larger A means that the market base of the MA channel is larger than that of the WS channel. Specifically, under Model RC, with a larger A , $l < A$ becomes easier. Therefore, it is interesting to infer that a larger

MA channel market base may induce the supply chain to strengthen channels when the presence of the WS channel increases the demand of the MA channel. On the contrary, under Model CR, with a larger A , $g < \frac{1}{A}$ becomes easier. That is to say, the supply chain will be motivated to delink channels when the market potential of the MA channel becomes larger.

3.5.3 Further Enhancing FET by Blockchain Technology

In the above analyses, we know that by investing in FET, the e-tailer can improve demand forecast which can improve its own performance as well as the e-commerce supply chain system's expected profit. In this extended analysis, suppose that the e-tailer can improve the efficiency of FET investment by the use of innovative technology.

To be very specific, by investing in blockchain technology as an infrastructure technology, the e-tailer can directly improve the efficiency of FET investment because information is more transparent, data are genuine and hence data quality is higher (Choi and Luo 2019; Choi et al. 2019; Niu et al. 2022). This facilitates the performance of demand planning module (which includes demand forecasting (Sharma 2019)), which is commonly present in a commercial enterprise system. This is exactly what Chainyard.com commented in its online article "How blockchain can solve demand forecasting problems" dated 20 Nov 2019: "*The significantly improved data quality leads to equally significant value when it comes to demand forecasting... That's because blockchain enables data safety and security, which affects demand forecasting in two important ways: 1. Creating trusted network-wide data...; 2. Keeping proprietary data separate and secure...*"¹⁹ These all relate to the infrastructure which means using blockchain can help establish a better "systems platform" to let the demand planning module conduct demand forecasting.

However, using blockchain also means increasing the per transaction cost as the use of blockchain as a distributed ledger incurs a per transaction cost (e.g., establishing the hash tag and the block). We represent this per transaction addition cost by δ . Plus, there is a fixed per period operations fee for blockchain T . To derive the analytically tractable closed form result, we assume that the cost for FET

¹⁹ <https://chainyard.com/how-blockchain-can-solve-demand-forecasting-problems/> (accessed 14 June 2021)

takes the quadratic form (see Example 1 in Table 3.5): $K(\theta) = \beta\theta^2 / 2$, and the forecast improvement is linear: $\varepsilon(\theta) = 1 - \theta$. With blockchain, the same forecast improvement can be made with a lower cost (compared to the case without blockchain) and we denote the FET investment cost function as: $\hat{K}(\theta) = \hat{\beta}\theta^2 / 2$, where $\hat{\beta} < \beta$.

Without blockchain, the optimal expected profit of the retailer under the decentralized case is:

$$\Pi_R^{\overline{BCT}^*} = (p - w) \left(\frac{a + \alpha + a\lambda + \alpha\gamma}{1 - \lambda\gamma} \right) + SB_R \left(\frac{SB_R - 2\beta}{2\beta} \right). \quad (3.7)$$

With blockchain, the optimal expected profit of the retailer under the decentralized case is:

$$\Pi_R^{BCT^*} = (p - w - \delta) \left(\frac{a + \alpha + a\lambda + \alpha\gamma}{1 - \lambda\gamma} \right) + SB_R^{BCT} \left(\frac{SB_R^{BCT} - 2\hat{\beta}}{2\hat{\beta}} \right) - T, \quad (3.8)$$

$$\text{where } B_R^{BCT} = (p - v - \delta) \phi \left[\Phi^{-1} \left(\frac{p - w - \delta}{p - v - \delta} \right) \right]. \quad (3.9)$$

Without blockchain, the optimal expected profit of the e-commerce supply chain under the coordinated (or centralized) case is listed below:

$$\Pi_{SC}^{\overline{BCT}^*} = (p - c) \left(\frac{a + \alpha + a\lambda + \alpha\gamma}{1 - \lambda\gamma} \right) + SB_{SC} \left(\frac{SB_{SC} - 2\beta}{2\beta} \right). \quad (3.10)$$

With blockchain, the optimal expected profit of the e-commerce supply chain under the coordinated (or centralized) case is given as follows:

$$\Pi_{SC}^{BCT^*} = (p - c - \delta) \left(\frac{a + \alpha + a\lambda + \alpha\gamma}{1 - \lambda\gamma} \right) + SB_{SC}^{BCT} \left(\frac{SB_{SC}^{BCT} - 2\hat{\beta}}{2\hat{\beta}} \right) - T, \quad (3.11)$$

$$\text{where } B_{SC}^{BCT} = (p - v - \delta) \phi \left[\Phi^{-1} \left(\frac{p - c - \delta}{p - v - \delta} \right) \right]. \quad (3.12)$$

Define:

$$\bar{T}_R = -\delta \left(\frac{a + \alpha + a\lambda + \alpha\gamma}{1 - \lambda\gamma} \right) + S \left[B_R^{BCT} \left(\frac{SB_R^{BCT} - 2\hat{\beta}}{2\hat{\beta}} \right) - B_R \left(\frac{SB_R - 2\beta}{2\beta} \right) \right], \quad (3.13)$$

$$\bar{T}_{SC} = -\delta \left(\frac{a + \alpha + a\lambda + \alpha\gamma}{1 - \lambda\gamma} \right) + S \left[B_{SC}^{BCT} \left(\frac{SB_{SC}^{BCT} - 2\hat{\beta}}{2\hat{\beta}} \right) - B_{SC} \left(\frac{SB_{SC} - 2\beta}{2\beta} \right) \right]. \quad (3.14)$$

Studying the expected profits of the retailer under the decentralized case and the coordinated e-commerce supply chain case, we have Proposition 3.8.

Proposition 3.8 (blockchain). *(a) Under the decentralized e-commerce supply chain, the e-tailer should implement the blockchain technology if $T < \bar{T}_R$. For the centralized (coordinated) e-commerce supply chain system, it is beneficial to implement the blockchain technology if $T < \bar{T}_{SC}$. (b) The use of blockchain or not does not affect the optimal decisions on “delink channels” or “strengthen cross-channel influences”.*

The results in Proposition 3.8a are rather intuitive. Yet, they provide the guidance to operations managers to decide whether and when to implement the blockchain technology to improve the FET investment efficiency. Under both the decentralized and centralized cases, if the per period operations cost for using blockchain is sufficiently small, it will be optimal to implement blockchain.

If it is optimal to use blockchain, when we check the impacts brought by changes of the cross-channel influences, we will find that the same pattern as in the cases without blockchain appears. Thus, the optimal “delink” or “strengthen” decision on cross-channel influences remains unchanged by the presence of the blockchain. We summarize the results in Proposition 3.8b. Proposition 3.8b is a neat result while it does carry a very important meaning. Since the optimal decision on “delink” or “strengthen” relates to the design of the mobile app and/or the website, if the e-tailer finds that it is optimal to improve the FET investment efficiency by using blockchain technology, it does not need to worry about whether there is a need to redesign the mobile app or website because blockchain does not play a role.

3.6 Summary of this Chapter

3.6.1 Major Findings

Today, it is well-known that e-commerce has entered the mobile era in which consumers love to integrate their shopping decision and experience with smart phones and mobile apps. In real world business operations, many brands have developed mobile apps for different purposes and allow consumers to purchase through both mobile-app (MA) and website (WS) channels. Based on real

world observations, we have identified that demand from one online channel may increase (called *channel reinforcement effect*) or decrease the demand from the other online channel (called the *channel cannibalization effect*), and the influences need not to be symmetric. In this work, we have analytically examined a dual channel e-commerce supply chain consisting of a retailer (i.e., e-tailer) and a manufacturer selling a forthcoming fashion product. Our first focal point is on the inventory management practices. Thus, we have considered the scenario in which the e-tailer can adopt risk pooling and invest in forecast-enhancement technology (FET) to improve inventory management. We have analytically derived the optimal inventory decision and investment level for FET. We have then revealed that depending on four different mode cases, when the magnitude of cross-channel influence increases, the impacts on the optimal inventory decision as well as performances of the e-commerce supply chain and its agents vary significantly; however, it has no impact on the optimal FET decision. We have then explored the use of supply chain contracts to achieve the dual channel e-commerce supply chain coordination under a Nash bargaining framework. We have further examined how cross-channel influence affects the contract setting. We have generated insights regarding whether it is optimal to “strengthen” or “weaken” the channel influences by adding links or removing links (i.e. “delinking”). Last but not least, we have studied the potential use of blockchain to improve effectiveness of FET investment and found that using blockchain or not does not affect the optimal MA and WS design decisions on “strengthen” or “delink”.

3.6.2 Managerial Implications

From the derived theoretical results, some managerial implications and action plans are proposed as follows.

Impacts brought by a larger magnitude of cross-channel influence: From Proposition 3.1, we understand that the e-tailer’s optimal ordering quantity and the corresponding optimal expected profit are affected by the magnitude of cross-channel influences. Owing to the features of the MA-WS dual channel, we have four models (Models RR, RC, CR and CC) capturing the directional channel reinforcement effect and channel cannibalization effect. However, it is interesting to observe that the optimal FET investment level is independent of the cross-channel influence. Thus, the e-tailer should

be very careful in noting which effect exists in its own e-commerce supply chain and then decides whether to increase or decrease the respective directional cross-channel influence. However, the e-tailer which plans to improve demand forecasting by deciding the respective optimal investment, the magnitudes of cross-channel influences are unimportant. Moreover, from Proposition 3.6, for the coordinated (or centralized) e-commerce supply chain system, the impacts brought by a larger magnitude of cross-channel influence on the centralized e-commerce supply chain's optimal ordering quantity and the corresponding optimal expected profit follow the same pattern as in the e-tailer's case under the decentralized uncoordinated supply chain setting (see Proposition 3.1).

Coordination: From Proposition 3.4 and Proposition 3.5, we know that the dual channel MA-WS e-commerce supply chain system under Nash bargaining can be coordinated by the TT, PS and MS contracts. First, the coordination settings of TT, PS, and MS contracts are affected by the bargaining power of the e-tailer and manufacturer. Second, for the coordinated (or centralized) e-commerce supply chain system, we uncover that impacts brought by a larger magnitude of cross-channel influence on the coordination contract parameters settings depend on the specific contract type. For the TT and PS contracts, there is no effect. For the MS contract, there are impacts which depend on the specific model under exploration (i.e., Models RR, RC, CR or CC).

Delink channels or strengthen cross-channel influences: For the coordinated e-commerce supply chain system, whether it is optimal to delink channels or strengthen cross-channel influences follows the results in Table 3.12 (see Proposition 3.7). First, the optimal "delink" or "strengthen" decisions relate to the specific directional cross-channel influence. For instance, under Model RC, it is always wise to delink the M2W (mobile app to website) channel while it is wise to strengthen the W2M (website to mobile app) channel if the M2W channel influence is sufficiently small. Second, whether to choose delink or strengthen depends on models. The corresponding pattern follows whether increasing or decreasing magnitude of a cross-channel influence will lead to a higher expected profit for the e-commerce supply chain system. Since the e-commerce supply chain is coordinated under Nash bargaining model, a higher supply chain expected profit directly implies a higher profit for each channel member. Third, for the models involving "C", i.e., the channel cannibalization effect (cf.: Model RC, Model CR, and Model CC), the optimal decision on whether it is wise to delink and

strengthen a particular cross-channel influence may depend on the size of the cross-channel influence. As a result, operations managers can decide the optimal “delink” or “strengthen” decision using the results in Table 3.12. The specific way to “delink” or “strengthen” can be done by the proper design of the mobile apps and websites (e.g., establishing, deleting, adding referrals, links, etc.) Furthermore, we argue that our findings regarding whether to “foster links” or “delink” between the WS sales channel and MA sales channel can also be used to explain many real world scenarios. As a matter of fact, we can observe different real world cases in which some of them have strong links between the two channels in both directions, some with links only in one direction and some are totally delinked.

Using blockchain: Whether the operations manager of the e-tailer should consider implementing blockchain highly depends on the per period fixed blockchain operations cost (for both the decentralized uncoordinated, and centralized/coordinated e-commerce supply chains). It is interesting to observe that the use of blockchain or not does not affect the optimal decisions on “delink” channels or “strengthen” cross-channel influences. This is an important result as it implies that the e-tailer can do two enhancements, implementing blockchain (to improve demand forecasting) and redesigning the website (with “delink and strengthen”), without worrying about one another as they are independent. Furthermore, if it is optimal to use blockchain, when we check the impacts brought by changes of the cross-channel influences, we will find that the same pattern as in the cases without blockchain appears.

Chapter 4 Channel Structure and Contracting in E-Platforms^{20,21}

4.1 Problem Statement

4.1.1 Research Background

Electronic platform (e-platform) service operations are very critical nowadays. Giant industrial e-platforms like eBay have recorded 10.3 billion US dollars in 2020²². One important service offered by these e-platforms is to act as a marketplace for other e-tailers to sell their products under their well-established e-commerce infrastructure. As a result, many e-tailers are selling through e-platforms. For instance, in Examples 1 and 2 (Figures 4.1 and 4.2), we can see that the world-leading international functional sportswear brand Adidas is selling through eBay²³ and Shopee²⁴. For brands of a caliber like Adidas, the main purpose of selling via eBay and Shopee is to establish one more sales channel and show its presence in major retail marketplaces. Figure 4.3 shows another scenario (Example 3) in which we can see different brands are selling their products towards the Chinese mainland market via JD.com²⁵. Over there, we can see many international brands (e.g., Adidas, Fila, Nike, etc.) as well as some other “local” brands (e.g., those in Chinese) selling there.

It is in fact very common to see that lots of well-established international brands which are selling online have already considered selling through e-platforms. The main reason is that this can potentially increase demand and also reduce the burden on operating the needed e-commerce information systems and website support. On the other hand, for the humble brands, selling through the e-platforms not only can enjoy the above benefits, but may also help enhance sales of their own direct-online sales channel if they have established it. Thus, e-platforms play a very pertinent role in e-commerce in potentially enticing the product demand of its direct sales channel. The existence of e-platforms induces channel influences (Chiu et al. 2018), which may be beneficial to the brands. On the other hand, entering into an e-platform may be detrimental to the brands. Selling through the large e-platform marketplace, such as Amazon and JD.com, always means competition with rivals. For example, consumers who visit Adidas’ products can be recommended to look through similar products offered by Nike, which results in the demand lost²⁶.

²⁰ A part of this chapter is summarized in “Siqin, T., Choi, T.M., Chung, S.H. (2022). Optimal e-tailing channel structure and service contracting in the platform era. *Transportation Research Part E*, 10.1016/j.tre.2022.102614”.

²¹ Abbreviations and notation used are only valid for this chapter.

²² <https://www.statista.com/statistics/507881/ebays-annual-net-revenue/> (accessed 2 December 2021)

²³ <https://www.ebay.com/str/adidas> (accessed 2 December 2021)

²⁴ <https://shopee.sg/adidassg> (accessed 10 December 2021)

²⁵ <https://mall.jd.com/index-120483.html> (accessed 2 December 2021)

²⁶ <https://digiday.com/media/how-adidas-is-using-apps-to-fuel-its-e-commerce-ambitions/> (accessed 2 November 2021)

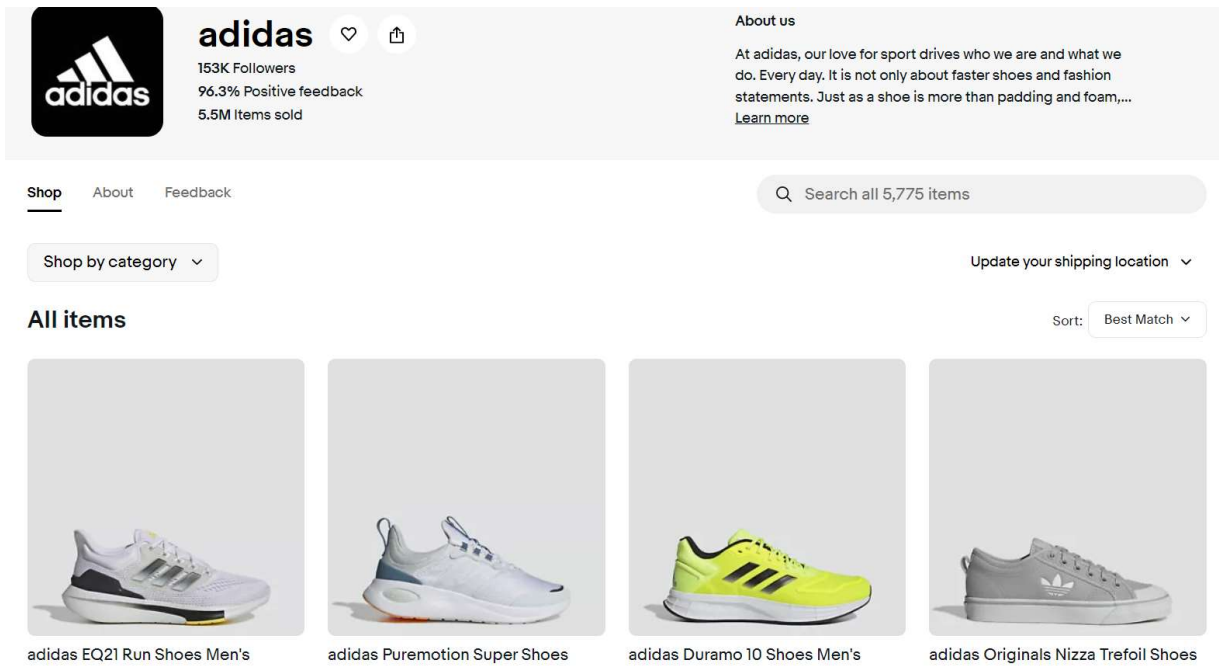


Figure 4.1. Example 1 of e-platform – Adidas selling its products on eBay³.

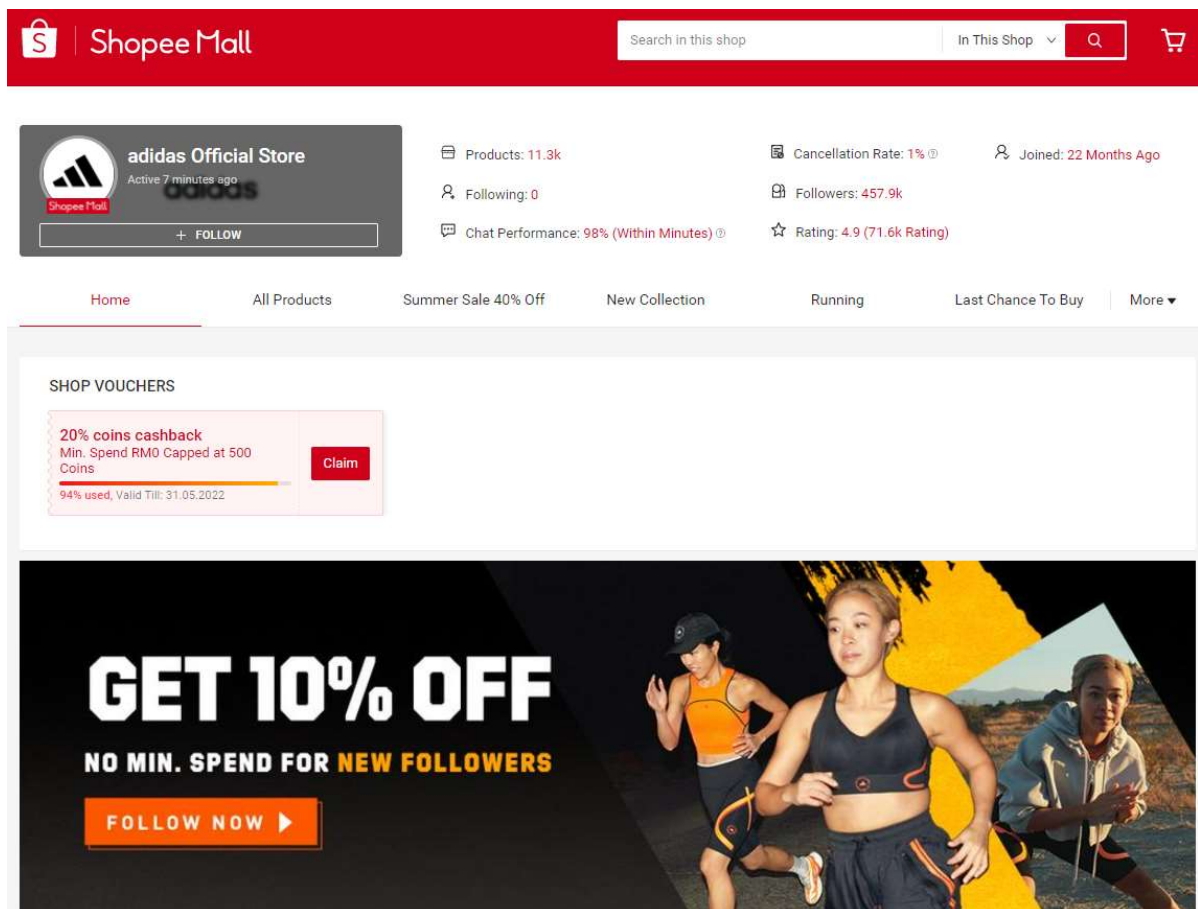


Figure 4.2. Example 2 of e-platform – Adidas selling its products on shopee.sg²⁷.

²⁷ <https://shopee.sg/adidassg> (accessed 2 December 2021)



Figure 4.3. Example 3 of e-platform – Various brands selling on JD.com²⁸.

Even though the potential benefits of selling through e-platform, there is no free lunch in the world and e-tailers usually need to pay a service fee. For instance, some e-platforms work like an agent and charge the e-tailers both a fixed fee and a revenue share of each product sold as the fee in its service contract (Wang et al. 2004). Considering the sales influences by e-platform channel and the service contracting with them, it is important for the e-tailers to coordinate these two sales channels. E-tailer's decisions include (i) Whether to use the e-platforms or not? (ii) If yes, should they still keep their direct-online (DO) sales channel? (iii) In response to the decision of e-tailers, what are the optimal service contracting schemes offered by e-platforms? Moreover, to evaluate the performance of the “e-tailer and e-platform” (ET-PF) system²⁹, we explore whether it can be optimized in performance? How good is the performance of the commonly seen service contract?

4.1.2 Research Questions and Major Findings

Motivated by the widely-observed industrial practice on e-platform operations in e-commerce, we build analytical models to explore the following research questions in this chapter.

1. For the e-tailer: How to determine whether it is optimal for the e-tailer to sell through an e-platform or not? If adopting an e-platform is beneficial, should the e-tailer keep the original direct-online channel or not?

²⁸ <https://channel.jd.com/children.html> (accessed 3 March 2021)

²⁹ The ET-PF system represents a system where the e-tailer and e-platform co-exist and have collaboration. For example, the e-tailer employs the e-platform to sell product only and the e-tailer sells products both direct online and through the e-platform.

2. For the platform: What is the optimal service contract so that its benefit can be maximized? What are the respective contract features? Can the commonly seen revenue-sharing-fixed-fee (RSF) service fee contract achieve “coordination” (i.e., robust systems optimization)?
3. Are the results robust if (i) the e-tailer makes product quality decisions, (ii) there exists an upstream manufacturer who produces the physical product and supplies to the e-tailer, and (iii) social welfare optimization is considered?

As we will show later on, addressing these questions yields various findings. First, we illustrate how the RSF service fee contract can maximize the ET-PF system. Second, we examine three models, namely the (pure) direct-online (DO) sales channel, the pure e-platform (PP) sales channel, and the dual direct-online and e-platform (DP) sales channel. For each model, the optimal pricing decision is derived. Third, an algorithm that helps achieve robust systems optimization (i.e., achieving systems optimization and allowing flexible profit allocation between the e-tailer and e-platform) is developed. Finally, we test robustness of the results by examining three extensions. For the extension in which the product is produced by a separate manufacturer and then supplied to the e-tailer, provided that a suitable supply contract is implemented to achieve “internal coordination” of this product supply chain, we show that all the findings in the basic models remain valid. For the extended analyses on consumer surplus and social welfare, we find that the RSF service contract can help achieve systems optimization in social welfare. For the extension when the e-tailer considers both product quality and retail product pricing decisions, we uncover that the RSF service contract fails to achieve robust systems optimization. As a remedial solution, we propose the use of a cost-sharing RSF service contract to help and show that it works well. Managerial implications are discussed.

4.2 Basic Models

We consider an e-tailer (ET) (the abbreviations are summarized in Table 4.1) who sells a product online to the market. The product’s unit selling price is p and the unit product cost is w , definitions of parameters used in basic models are shown in Table 4.2. In this work, despite we call it “e-tailer”, the company actually does both production and retailing and hence represents the product supply chain system³⁰. When the e-platform is employed, under its RSF contract, the required fixed service fee is

³⁰ We can further include an upstream manufacturer in the analysis while the result will remain the same. For the sake of simplicity and to derive more clean results, we use the simpler model in this sub-chapter and discuss the robustness in the extension (see Chapter 4.5.1).

ξ and the revenue share proportion is $\gamma = 1 - \phi$. In the following, we will consider three operational cases with respect to the selling channels. Figure 4.4 depicts them.

Figure 4.4. Operational structures of Model DO, Model PP and Model DP.

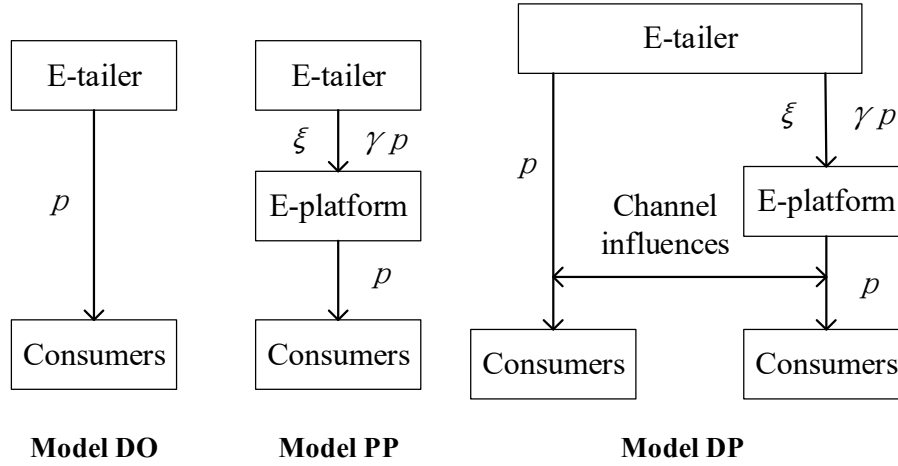


Table 4.1. The list of abbreviations employed in this chapter.

Abbreviation	Meaning
ET	E-tailer
PF	E-platform
DO	Direct-online
PP	Pure e-platform
DP	Direct-online and e-platform together
RS	Revenue sharing
RSF contract	Revenue-sharing fixed fee contract
ET-PF system	E-tailer and e-platform system
QDO	Direct-online (under the case with product quality as a decision)
QPP	Pure e-platform (under the case with product quality as a decision)
QDP	Direct-online and e-platform together (under the case with product quality as a decision)
MU	Manufacturer (extended model; Chapter 4.5.1)
ET-MU	E-tailer manufacturer (extended model; Chapter 4.5.2)
SR contract	Sales rebates contract
CS-RSF contract	Cost-sharing RSF contract
CS	Consumer surplus

4.2.1 Model DO

As a simple benchmark, under the simplest model in which the e-tailer sells directly online, we have Model DO. Demand of Model DO is given by $d_{DO} = a - bp$, where a is the market base for the direct online sales channel and b indicates the demand sensitivity of price. Note that the linear price-

dependent demand function is well-adopted in the literature (Chiu et al. 2018) and it is consistent with the case when consumers in the market possess the uniformly distributed product valuation (see Appendix (I-6)). Under Model DO, there is a unit operation cost for the online sales channel y and a fixed cost Z . It is easy to find that the e-tailer's profit function is given as follows:

$$\Pi_{ET}^{DO} = (p - w - y)(a - bp) - Z. \quad (4.1)$$

Checking the structural properties shows that Π_{ET}^{DO} is concave in p . Maximizing Π_{ET}^{DO} yields the optimal selling price: $\frac{d\Pi_{ET}^{DO}}{dp} = 0 \Rightarrow p_{ET}^{DO*} = \frac{a}{2b} + \frac{w+y}{2}$.

Table 4.2. Definitions of parameters of basic model (in this chapter).

Parameter	Meaning
p	The unit selling price of product, $p \geq 0$.
w	The unit product cost for the direct-online sales channel, $w \geq 0$.
a	The market base for the direct-online sales channel, $a \geq 0$.
b	The demand sensitivity of price for the direct-online sales channel, $0 \leq b \leq 1$.
y	The unit operations cost for the direct-online sales channel, $y \geq 0$.
Z	The fixed cost for operating the direct-online sales channel, $Z \geq 0$.
α	The market base for the e-platform channel, $\alpha \geq 0$.
β	The demand sensitivity of price for the e-platform channel, $0 \leq \beta \leq 1$.
c	The unit operations cost for the e-platform channel, $c \geq 0$.
ξ	The fixed service fee pays to the e-platform, $\xi > 0$.
γ	The proportion of revenue shares pay to the e-platform, $\gamma = 1 - \phi$, and $0 \leq \gamma \leq 1$.
ϕ	The proportion of revenue shares that the e-tailer takes, $\phi = 1 - \gamma$.
λ	The degree of channel influence on the direct-online sales channel when the e-platform channel presents, $-1 \leq \lambda \leq 1$.
l	The degree of channel influence on the e-platform channel when the direct-online sales channel presents, $-1 \leq l \leq 1$.

4.2.2 Model PP

Now, we consider Model PP in which the e-tailer gives up its own direct-online sales channel and sells solely via the e-platform (PF). Under Model PP, demand is given by $d_{pp} = \alpha - \beta p$, where α is the market base of the e-platform and β is the demand sensitivity of price. The e-tailer has to pay a fixed service fee ξ as well as a certain proportion γ of its revenue to the e-platform. The e-tailer's profit function under Model PP is given below:

$$\Pi_{ET}^{PP} = (\phi p - w)(\alpha - \beta p) - \xi, \quad (4.2)$$

where $\phi = 1 - \gamma$.

Furthermore, the e-platform's profit function under Model PP is:

$$\Pi_{PF}^{PP} = (\gamma p - c)(\alpha - \beta p) + \xi, \quad (4.3)$$

where c is the unit operations cost for the e-platform to support the business transaction.

Adding (4.2) and (4.3) together yields the total ET-PF system's benefit under Model PP:

$$\Pi_{SYS}^{PP} = \Pi_{ET}^{PP} + \Pi_{PF}^{PP}. \quad (4.4)$$

Checking the structural properties clearly shows that Π_{ET}^{PP} and Π_{SYS}^{PP} are both concave in p . Maximizing them yields the optimal selling prices for the e-tailer and system under Model PP,

respectively: $\frac{d\Pi_{ET}^{PP}}{dp} = 0 \Rightarrow p_{ET}^{PP*} = \frac{\alpha}{2\beta} + \frac{w}{2\phi}$, and $\frac{d\Pi_{SYS}^{PP}}{dp} = 0 \Rightarrow p_{SYS}^{PP*} = \frac{\alpha}{2\beta} + \frac{w+c}{2}$.

4.2.3 Model DP

Finally, we have Model DP which denotes the case when the e-tailer sells through both its own direct-online sales channel and the e-platform. In this case, the product demand includes two parts: demand for the direct-online channel and the demand for the e-platform channel. Note that to capture all possible relationships between market of the direct-online channel and e-platform channel, we do not restrict α and a . Moreover, there are channel influences for each part of demand since both sales channels co-exist (Chiu et al. 2018). We model channel influences as two types and we denote them by λ and l , which can be positive or negative (Choi. 2020). The demand of Model DP can be expressed as shown in (4.5):

$$d_{DP} = \underbrace{\{a - bp + \lambda(\alpha - \beta p)\}}_{\text{Direct-online sales}} + \underbrace{\{\alpha - \beta p + l(a - bp)\}}_{\text{E-platform sales}}, \quad (4.5)$$

Channel influence Channel influence

where λ and l are constants bounded between -1 and +1³¹.

In the demand model (3.5), we can clearly see that depending on whether λ and l are positive or negative, the impacts are different and "opposite". For example, when λ is positive (negative), it means the presence of e-platform sales channel increases (decreases) the demand of the direct-online

³¹ This bound indicates that the influence brought by the other sales channel on demand won't be bigger than the sales channel itself.

sales channel. For l , when it is positive (negative), it means the presence of direct-online sales channel increases (decreases) the demand of the e-platform sales channel. Note that the effect in general can be asymmetric, i.e., λ is positive (negative) and l is negative (positive). The presence of positive or negative λ and l would help capture the channel influence which is a key factor in affecting the optimal channel choice decisions and service contracting³².

Under Model DP, the profit functions of e-tailer, e-platform, and the ET-PF system are shown below:

$$\Pi_{ET}^{DP} = \{(p-w-y)(a-bp+\lambda(\alpha-\beta p))-Z\} + \{(\phi p-w)(\alpha-\beta p+l(a-bp))-\xi\}, \quad (4.6)$$

$$\Pi_{PF}^{DP} = (\gamma p-c)(\alpha-\beta p+l(a-bp))+\xi, \quad (4.7)$$

$$\Pi_{SYS}^{DP} = \Pi_{ET}^{DP} + \Pi_{PF}^{DP}. \quad (4.8)$$

Both Π_{ET}^{PP} and Π_{SYS}^{PP} are concave in p . Maximizing them by solving the corresponding first-order conditions yields the optimal selling prices for the e-tailer and system under Model DP, respectively

$$p_{ET}^{DP*} = \frac{w(\beta+lb)+\phi(\alpha+al)+(w+y)(b+\lambda\beta)+(a+\lambda\alpha)}{2[\phi(\beta+lb)+(b+\lambda\beta)]}, \text{ and}$$

$$p_{SYS}^{DP*} = \frac{(w+c)(\beta+lb)+(\alpha+al)+(w+y)(b+\lambda\beta)+(a+\lambda\alpha)}{2[(\beta+lb)+(b+\lambda\beta)]}.$$

From the optimal selling prices, we can see that the revenue share parameter ϕ is present in p_{ET}^{DP*} but not in p_{SYS}^{DP*} . As a result, adjusting ϕ becomes a probable measure to make p_{ET}^{DP*} the same as p_{SYS}^{DP*} . In Model DP, the co-existence of e-tailer's direct selling channel and e-platform selling channel affects the demand of two channels. This also affects the optimal pricing decisions of both the e-tailer and the overall supply chain system.

Corollary 4.1. *Under Model DP: (i) p_{ET}^{DP*} and p_{SYS}^{DP*} are increasing in λ when a is sufficiently small while decreasing in λ when a is sufficiently large; (ii) However, p_{ET}^{DP*} and p_{SYS}^{DP*} are decreasing in l when a is sufficiently small while increasing in l when a is sufficiently large, except for the case when $\lambda-\gamma+1 < 0$.*

Corollary 4.1 indicates that the optimal pricing decisions are affected by channel influences under Model DP. The effects highly depend on the market base a . To be specific, a high channel influence on the e-tailer's direct online channel yields higher prices when the market base of that channel is relatively small. On the other hand, the higher channel influence on the e-platform channel leads to lower prices when the market base of the direct selling channel is relatively small. The market base is

³² Moreover, the relationship between λ and l has not been restricted to make our model more applicable.

hence a critical factor determining how the optimal prices are affected by the channel influences. This finding is important for the e-tailer and ET-PF system to make the optimal pricing decisions when the e-platform is employed.

4.3 Robust Systems Optimization

In Chapter 4.2, we have already built the profit functions and derived the optimal pricing decisions for a given RSF service contract. In the following, we first prove that the RSF service contract is a systems optimization contract which can flexibly divide the profit of the supply chain system between the related parties. Note that systems optimization here is similar in meaning with supply chain coordination in the standard operations management literature. The term “robust” means that we can flexibly divide the system’s profit in an arbitrary proportion.

First of all, under Model PP, $p_{ET}^{PP*} = p_{SYS}^{PP*}$, which means setting $\gamma = \gamma^{PP*}$ where $\gamma^{PP*} = \frac{c}{w+c}$ in the RSF service contract will make the e-tailer price the product in a way which is the best for the ET-PF system under Model PP.

For a notational purpose, we define some notation in the following: $\eta = \beta + lb$, $\theta = \alpha + al$, $J = 2(b + \lambda\beta)$, $K = w(\beta + lb) + (w + y)(b + \lambda\beta) + (a + \lambda\alpha)$.

It is straightforward to find that $\gamma = \gamma^{DP*}$ where $\gamma^{DP*} = \frac{(2\eta + J)c\eta}{2\eta(K + c\eta) - \theta J}$ when $p_{ET}^{DP*} = p_{SYS}^{DP*}$ in the RSF service contract. This proportion of revenue shares will help entice the e-tailer to price the product in a way which is the best for the ET-PF system under Model DP.

Definition 4.1. *An RSF service contract with parameters γ and ξ is called a flexible systems optimization contract under Model i , for $i \in (PP, DP)$, if and only if (i) it can entice the e-tailer to price the product in a way which is the best as the ET-PF system; and (ii) it can arbitrarily allocate the ET-PF system’s profit between the e-tailer and e-platform in any proportion.*

Definition 4.1 follows the popular definition Cachon and Lariviere (2005) and Gan et al. (2005) for “robust supply chain coordination” while as the e-platform is a service provider and the e-tailer in fact represents the e-supply chain for the physical product, we do not call it “supply chain coordination”.

Considering the e-tailer and e-platform have the reservation profits (i.e., minimum profit requirements) of Ω_{ET} and Ω_{PF} , respectively. The e-tailer and e-platform will be willing to engage in the service contract if their respective reservation profits can be achieved. To have a meaningful analysis and avoid trivial cases, we require: $\Pi_{SYS}^{PP}(p_{SYS}^{PP*}) \geq \Omega_{ET} + \Omega_{PF}$ and $\Pi_{SYS}^{DP}(p_{SYS}^{DP*}) \geq \Omega_{ET} + \Omega_{PF}$,

which guarantees that the e-tailer and e-platform are both reasonable in setting their reservation profits with which their sum will be no larger than the maximum achievable profit of the whole ET-PF system.

Define:

$$\Omega_{ET}^{PP*} = ((1 - \gamma^{PP*})p_{SYS}^{PP*} - w)(\alpha - \beta p_{SYS}^{PP*}), \quad (4.9)$$

$$\Omega_{PF}^{PP*} = (\gamma^{PP*} p_{SYS}^{PP*} - c)(\alpha - \beta p_{SYS}^{PP*}), \quad (4.10)$$

$$\Omega_{ET}^{DP*} = \{(p_{SYS}^{DP*} - w - y)(a - bp_{SYS}^{DP*} + \lambda(\alpha - \beta p_{SYS}^{DP*}) - Z) + \{(1 - \gamma^{DP*})p_{SYS}^{DP*} - w)(\alpha - \beta p_{SYS}^{DP*} + l(a - bp_{SYS}^{DP*}))\}, \quad (4.11)$$

$$\Omega_{PF}^{DP*} = (\gamma^{DP*} p_{SYS}^{DP*} - c)(\alpha - \beta p_{SYS}^{DP*} + l(a - bp_{SYS}^{DP*})). \quad (4.12)$$

Proposition 4.1. (a) *The RSF service contract is a flexible systems optimization contract under both Model i, for $i \in (PP, DP)$. (b) To achieve ET-PF systems optimization under Model i, for $i \in (PP, DP)$, the RSF service contract parameters should be set as follows: $\gamma = \gamma^{i*}$ and $\xi = \xi^{i*}$ in which $\Omega_{PF} - \Omega_{PF}^{i*} \leq \xi^{i*} \leq \Omega_{ET}^{i*} - \Omega_{ET}$.*

Proposition 4.1 shows that under Mode PP and Model DP in which the e-platform is involved, robust systems optimization can be achieved by the RSF contract. To achieve systems optimization under the RSF contract, the revenue sharing parameter has to be set to be a specific number (i.e., there is no freedom). Luckily, the fixed service fee gives the needed degree of freedom and flexibility to allocate the systems profit arbitrarily between the e-tailer and e-platform. This is an important result as it will help a lot for us to derive the optimal channel choice decision for the e-tailer. It is because we now can first consider whether the optimal ET-PF systems' profit is high or low in justifying whether to use the e-platform instead of exploring the profits of e-tailer and e-platform separately. Moreover, observing ξ^* , we find that the degree of freedom of RSF to allocate the system profit will be weakened when the e-platform takes a higher proportion of profit from the e-tailer. Based on the finding of Proposition 4.1, we have Proposition 4.2.

Proposition 4.2. *For the e-tailer, whether to use the e-platform can be judged from the systems perspective: If $\max(\Pi_{SYS}^{PP*}, \Pi_{SYS}^{DP*}) \leq \Pi_{SYS}^{DO*}$, then the optimal channel choice is DO; otherwise, the optimal channel choice is either PP or DP, in which the e-platform is employed.*

Proposition 4.2 is important because it means we can determine the optimal channel choice decision before determining the optimal RSF service contract parameters. This not only helps develop an easy logic to implement an optimization algorithm, but also makes one point clear: The optimal channel choice decision for the e-tailer is also the same as the optimal channel choice decision for the ET-PF system.

4.4 An Algorithm: Optimal Decisions

In Chapter 4.3, we have proven that the RSF service contract can achieve robust systems optimization and also shown that the e-tailer's optimal decision on whether to employ the e-platform service or not can be judged from the ET-PF systems perspective. This helps us derive the algorithm to determine the optimal channel choice for the e-tailer.

Define:

$$\Pi_{SYS}^{DO*} = \Pi_{ET}^{DO}(p_{ET}^{DO*}),^{33} \quad (4.13)$$

$$\Pi_{SYS}^{PP*} = \Pi_{SYS}^{PP}(p_{SYS}^{PP*}), \quad (4.14)$$

$$\Pi_{SYS}^{DP*} = \Pi_{SYS}^{DP}(p_{SYS}^{DP*}). \quad (4.15)$$

Table 4.3. Algorithm 1: The algorithm to determine the optimal channel choice and RSF service contract parameters.

Algorithm 1	
Stages	Steps
Stage 1	<p><i>Step 1.1:</i> Find Π_{SYS}^{k*}, for $k \in (DO, PP, DP)$.</p> <p><i>Step 1.2:</i> If $\max(\Pi_{SYS}^{PP*}, \Pi_{SYS}^{DP*}) \leq \Pi_{SYS}^{DO*}$, then the optimal channel choice is DO. Set the optimal price as p_{ET}^{DO*} and stop. Otherwise, proceed to Step 2.1.</p>
Stage 2	<p><i>Step 2.1:</i> Compare between Π_{SYS}^{PP*} and Π_{SYS}^{DP*}, if $\Pi_{SYS}^{PP*} > \Pi_{SYS}^{DP*}$, then the optimal channel choice is PP. If $\Pi_{SYS}^{PP*} < \Pi_{SYS}^{DP*}$, then the optimal channel choice is DP. If $\Pi_{SYS}^{PP*} = \Pi_{SYS}^{DP*}$, then the optimal channel choice is either PP and DP. Move to Step 3.1.</p>
Stage 3	<p><i>With the optimal channel choice determined in Stage 2:</i></p> <p><i>Step 3.1:</i> Set the optimal RSF service contract parameters following Proposition 4.1. The exact values depend on the relative bargaining powers of the e-tailer and e-platform.</p> <p><i>Step 3.2:</i> Set the optimal product selling price in the market under the optimal RSF service contract parameters and channel choice.</p>

Algorithm 1 is easy to use. Stage 1 tests to see if it is wise to use the e-platform. In Step 1.2, if $\max(\Pi_{SYS}^{PP*}, \Pi_{SYS}^{DP*}) \leq \Pi_{SYS}^{DO*}$, it means using the e-platform will not bring any benefit in profit. Thus, choosing the direct-online sales channel is the optimal choice. Otherwise, using the e-platform is beneficial. Thus, Stage 2 compares Model PP and Model DP and identifies the best one from the ET-PF systems perspective; then, after determining the optimal model, in Stage 3, we determine the respective optimal RSF service contract parameters using the theoretical results derived in Proposition

³³ Under Model DO, the e-platform does not play a role. Thus, the system only includes the e-tailer.

4.1. Finally, we determine the optimal product selling price with respect to the optimal RSF service contract parameters under the optimal channel choice model.

4.5 Extensions

In this sub-chapter, to enhance research rigors and generate deeper insights, we conduct robustness checking with the goal of checking whether our findings in the earlier sub-chapters would still hold when there are changes in the model.

4.5.1 Including a Separate Upstream Manufacturer

In Chapter 4.2, we consider the case when the e-tailer both produces and sells the product to the market, i.e., it acts as the whole product supply chain. In general, we can have another party to act as a manufacturer. If it is the case, will the results hold? In this extension, we examine the situation including a separate upstream manufacturer.

We consider the presence of a separate manufacturer who produces the product at a unit cost of w and supplies the product to the e-tailer as a wholesale price g . In order to overcome the double marginalization effect in the product supply chain, the manufacturer (MU) offers the e-tailer a sales rebate which is a certain percentage r of the product retail price p . In other words, a sales rebate (SR) contract is in place with parameters g and r . It is easy to prove that the ET-MU supply chain can be internally optimized (i.e., coordinated) with a flexible division of profit under the SR contract. In this case, when the ET-MU supply chain is first internally optimized, then the ET-MU supply chain system can act as a single unit, and the detailed mechanism of Algorithm 1 to determine the optimal channel choice as well as the optimal RSF service contract remains valid. We summarize the findings in Proposition 4.3.

Proposition 4.3. *If the product supply chain includes an upstream manufacturer and an e-tailer, under a SR contract, the product supply chain can be internally coordinated by setting $g=(1+r)w$ and different (g, r) pairs will yield different profit divisions between the manufacturer and e-tailer. Then, the detailed mechanism of Algorithm 1 to determine the optimal decisions remain valid.*

Proposition 4.3 shows the robustness testing result for the case when there is a separate manufacturer in the product supply chain. As a remark, in addition to the SR contract, it is easy to find that the profit-sharing contract and two-part tariff contract can also achieve internal coordination for the product supply chain. However, the revenue sharing contract fails. Here, the revenue sharing contract fails because the required shared rate will become negative which basically becomes the SR contract.

4.5.2 Consumer Surplus and Social Welfare Optimization

In Chapter 4.2 and Chapter 4.3, we have explored the optimal channel choice from the perspective of a pure profit-oriented e-tailer and ET-PF system. In this part, we proceed to consider the consumer surplus (CS) and go further to explore the social welfare (SW) optimization in dual channel operations (Xu et al. 2021).

A. Consumer surplus

According to Chapter 4.2, the price threshold \bar{p}_i for Model $i \in (DO, DP, PP)$ in which the product demand equal to zero can be derived as follows:

Under Model DO, $d_{DO} = a - bp = 0 \Rightarrow \bar{p}_{DO} = \frac{a}{b}$; under Model PP, $d_{PP} = \alpha - \beta p \Rightarrow \bar{p}_{PP} = \frac{\alpha}{\beta}$; under

Model DP, $d_{DP} = \{a - bp + \lambda(\alpha - \beta p)\} + \{\alpha - \beta p + l(a - bp)\} \Rightarrow \bar{p}_{DP} = \frac{a(1+l) + \alpha(1+\lambda)}{b(1+l) + \beta(1+\lambda)}$.

Following Hitt and Brynjolfsson (1996), we adopt the demand curve approach to calculate consumer surplus, which is measured by the amount of price that a consumer is willing to spend on a product³⁴. Then the consumer surplus can be expressed as follows:

$$\text{For the e-tailer: } CS_{ET}^i = \frac{1}{2} d_i(p_{ET}^{i*})(\bar{p}_i - p_{ET}^{i*}), \quad (4.16)$$

$$\text{For the ET-PF system: } CS_{SYS}^i = \frac{1}{2} d_i(p_{SYS}^{i*})(\bar{p}_i - p_{SYS}^{i*}). \quad (4.17)$$

Based on the CS expressions derived above, we examine whether the e-tailer uses the e-platform, and which model is optimal for the e-tailer according to consumer surplus. To be specific, the systems' consumer surplus equals CS_{ET}^{DO} for Model DO.

Proposition 4.4. *For the e-tailer, whether to adopt the e-platform can be judged from the view of systems' profit and consumer surplus simultaneously. If $\max(CS_{SYS}^{PP}, CS_{SYS}^{DP}) \leq CS_{SYS}^{DO}$ and $\max(\Pi_{SYS}^{PP*}, \Pi_{SYS}^{DP*}) \leq \Pi_{SYS}^{DO*}$, then the optimal channel choice is Model DO for both the e-tailer and consumers; If $\min(CS_{SYS}^{PP}, CS_{SYS}^{DP}) > CS_{SYS}^{DO}$ and $\min(\Pi_{SYS}^{PP*}, \Pi_{SYS}^{DP*}) > \Pi_{SYS}^{DO*}$, the optimal choice is either Model PP or DP, in which adopting e-platform is the better choice for both the e-tailer and consumers.*

Proposition 4.4 is crucial for the ET-PF system to determine the optimal channel choice with the consideration of both the ET-PF system's profit and consumer surplus³⁵. Observe that nowadays, with

³⁴ The approach to derive consumer surplus is different from the approach where utility function is deployed as we capture the market demand using the linear demand function.

³⁵ In Proposition 4.2, we state that the optimal decision for the e-tailer is the same as the optimal decision for the ET-PF system.

the emphasis on corporate social responsibility, both business profit and consumers are critical in affecting optimal decision making. It is thus increasingly important to consider whether consumers are beneficial or not when making business decisions. Moreover, it is critical to explore the conditions of one possible case in which Model i is optimal for consumers in more detail. As there are various possible cases, we only give an example in Appendix (I-6).

B. Social welfare optimization

In this part, we consider the case that the ET-PF system determines product price to maximize its social welfare, and using the RSF contract we mentioned in the basic model to achieve social welfare optimization. This optimization problem is valid for the companies which are socially responsible operations. In the following, we first show the expressions of social welfare (SW) under Model i for $i \in (DO, PP, DP)$. To be specific, we adopt a common method to construct the social welfare expressions, which is to use the sum of profit and consumer surplus see (Benjaafar et al. 2018). Moreover, to be more precise, we consider the weighted sum function, denote h and $(1-h)$ as respective proportions that consumer surplus and profits take, and $h \in [0, 1]$.

Under Model DO, it can be observed that the social welfare function of ET-PF system is the same as that of the e-tailer, it is given in (4.18).

$$SW_{SYS}^{DO} = SW_{ET}^{DO} = h\left(\frac{1}{2}d_{DO}(\bar{p}_{DO} - p)\right) + (1-h)\Pi_{ET}^{DO}. \quad (4.18)$$

Note that (4.18) is concave, and solving the first-order condition yields:

$$p_{ET}^{DO, SW*} = \frac{a(2h-1) + b(h-1)(w+y)}{b(3h-2)}.$$

Under Model PP, the social welfare of the e-tailer and ET-PF system are shown in (4.19) and (4.20):

$$SW_{ET}^{PP} = h\left(\frac{1}{2}d_{PP}(\bar{p}_{PP} - p)\right) + (1-h)\Pi_{ET}^{PP}, \quad (4.19)$$

$$SW_{SYS}^{PP} = h\left(\frac{1}{2}d_{PP}(\bar{p}_{PP} - p)\right) + (1-h)\Pi_{SYS}^{PP}. \quad (4.20)$$

Observe that in (4.19), social welfare is the objective of the e-tailer when it is a socially responsible operation and hence its goal is to maximize not just its own profit but the social welfare (including consumer surplus). From (4.19) and (4.20), it is straightforward to derive the optimal price to be:

$$p_{ET}^{PP, SW*} = \frac{-w\beta - \alpha\phi + h(\alpha + w\beta + \alpha\phi)}{\beta(h - 2\phi + 2h\phi)} \quad \text{and} \quad p_{SYS}^{PP, SW*} = \frac{(-1 + 2h)\alpha + (-1 + h)(c + w)\beta}{(-2 + 3h)\beta}.$$

Under Model DP, it is obvious that the expressions of social welfare (given in (4.21) and (4.22)) become more complex owing to the existence of channel influences.

$$SW_{ET}^{DP} = h\left(\frac{1}{2}d_{DP}(\bar{p}_{DP} - p)\right) + (1-h)\Pi_{ET}^{DP}, \quad (4.21)$$

$$SW_{SYS}^{DP} = h\left(\frac{1}{2}d_{DP}(\bar{p}_{DP} - p)\right) + (1-h)\Pi_{SYS}^{DP}. \quad (4.22)$$

Maximizing (4.21) and (4.22), we have the following closed-form expressions for the optimal

$$\text{prices: } p_{ET}^{DP,SW*} = \frac{\left[\begin{array}{l} b(-1+h)(w+lw+y) + w\beta(-1+h-\lambda+h\lambda) + h\alpha(1+2\lambda) + \\ \beta\lambda(hy-y) + (-1+h)\alpha\phi + a(-1-\lambda+h(2+l) + (-1+h)l\phi) \end{array} \right]}{b(-2+h(3+l) + 2(-1+h)l\phi) + \beta(-2(\lambda+\phi) + h(1+3\lambda+2\phi))},$$

$$p_{SYS}^{DP,SW*} = \frac{\left[\begin{array}{l} a(-1+2h)(1+l) + b(-1+h)T + \alpha(2h-1) + c\beta(h-1) \\ + w\beta(h-1) + \lambda((-1+2h)\alpha + (-1+h)(w+y)\beta) \end{array} \right]}{(-2+3h)(b+bl+\beta+\beta\lambda)},$$

where $T = w + y + l(c + w)$.

Based on the SW expressions derived above, whether the RSF contract can achieve social welfare systems optimization can be explored, and we first give Definition 4.2.

Definition 4.2. *An RSF service contract with parameter γ and ξ can achieve robust social welfare systems optimization under Model i , for $i \in (PP, DP)$, if and only if (i) it can satisfy $p_{SYS}^{i,SW*} = p_{ET}^{i,SW*}$; (ii) it can allocate the ET-PF system's social welfare between the e-tailer and e-platform in any proportion.*

Definition 4.2 follows the concept of robust systems optimization in Definition 4.1, and we call it the “robust social welfare systems optimization”. Here, when $p_{SYS}^{PP,SW*} = p_{ET}^{PP,SW*}$ and $p_{SYS}^{DP,SW*} = p_{ET}^{DP,SW*}$, the corresponding $\gamma = \gamma_{SW}^{PP*}$ and $\gamma = \gamma_{SW}^{DP*}$ of RSF contract can be derived respectively to make the RSF contract meet the requirements of systems optimization under Model PP and Model DP.

$$\text{Firstly, observe that } p_{SYS}^{PP,SW*} = p_{ET}^{PP,SW*} \Rightarrow \gamma_{SW}^{PP*} = \frac{(3h-2)((1-2h)(1-p)\alpha + (1-h)(c+w-pw)\beta)}{-(1-h)((2-2p+h(3p-4))\alpha + 2(1-h)(c+w)\beta)},$$

which meets the constraint of Model PP. Under Model DP, note that $p_{SYS}^{DP,SW*} = p_{ET}^{DP,SW*} \Rightarrow$

$$\gamma_{SW}^{DP*} = \frac{c(3h-2)(bl+\beta)(bl+\beta+b+\beta\lambda)}{\left[\begin{array}{l} 2b^2l(-1+h)T + a(bhl(1+l) - \beta(M-h(1+l))) + \\ b(2(-1+h)\beta(T+l(c+w) + \lambda l(w+y)) + \alpha(M+hl(1+\lambda))) + \beta(-2\beta P + h(\alpha(1+\lambda) + 2\beta P)) \end{array} \right]},$$

where $P = c + w + \lambda(w + y)$ and $M = 2 - 2l\lambda - 3h + 3hl\lambda$, which achieves the robust social welfare system optimization.

On the other hand, the e-tailer and e-platform both have their “reservation social welfares” (RSWs), i.e., Ω_{ET}^{SW} and Ω_{PF}^{SW} , respectively. Note that Ω_{ET}^{SW} and Ω_{PF}^{SW} represent the minimum acceptable levels of social welfare that a socially responsible e-tailer and e-platform will set for their own operations. They will have to be satisfied with the RSF contract or else they will not work together. Hence, it is necessary to set an optimal ξ_{SW}^i for the RSF contract. Also, we assume that $SW_{SYS}^{PP}(p_{SYS}^{PP*}) \geq \Omega_{ET}^{SW} + \Omega_{PF}^{SW}$ and $SW_{SYS}^{DP}(p_{SYS}^{DP*}) \geq \Omega_{ET}^{SW} + \Omega_{PF}^{SW}$ to make sure that the social welfare of ET-PF system will always be larger than the sum of social welfare of e-tailer and e-platform so that a solution exists.

Define:

$$\Omega_{ET}^{PP,SW*} = \frac{h}{1-h} \left(\frac{1}{2} d_{PP}(\bar{p}_{PP} - p_{SYS}^{PP,SW*}) \right) + ((1 - \gamma^{PP*}) p_{SYS}^{PP,SW*} - w)(\alpha - \beta p_{SYS}^{PP,SW*}), \quad (4.23)$$

$$\Omega_{PF}^{PP,SW*} = \frac{h}{1-h} \left(\frac{1}{2} d_{PP}(\bar{p}_{PP} - p_{SYS}^{PP,SW*}) \right) + (\gamma^{PP*} p_{SYS}^{PP,SW*} - c)(\alpha - \beta p_{SYS}^{PP,SW*}), \quad (4.24)$$

$$\begin{aligned} \Omega_{ET}^{DP,SW*} &= \frac{h}{1-h} \left(\frac{1}{2} d_{DP}(p_{SYS}^{DP,SW*})(\bar{p}_{DP} - p_{SYS}^{DP,SW*}) \right) + \{(\gamma^{DP*} p_{SYS}^{DP,SW*} - w - y)(a - b p_{SYS}^{DP,SW*} + \lambda(\alpha - \beta p_{SYS}^{DP,SW*})) - Z\} \\ &\quad + \{(\phi p_{SYS}^{DP,SW*} - w)(\alpha - \beta p_{SYS}^{DP,SW*} + l(a - b p_{SYS}^{DP,SW*}))\}, \end{aligned} \quad (4.25)$$

$$\Omega_{PF}^{DP,SW*} = \frac{h}{1-h} \left(\frac{1}{2} ((\alpha - \beta p + l(a - b p_{SYS}^{DP,SW*}))) (\bar{p}_{PP} - p_{SYS}^{DP,SW*}) \right) + \{(\gamma^{DP*} p_{SYS}^{DP,SW*} - c)(\alpha - \beta p + l(a - b p_{SYS}^{DP,SW*}))\}. \quad (4.26)$$

Since social welfare is a weighted combination of profit and consumer surplus, the proportion factor h is critical. We thus propose Proposition 4.5 to uncover its role.

Proposition 4.5 (i) When $h=0$, robust social welfare systems optimization is the same as robust (profit only) systems optimization under Model i , for $i \in (PP, DP)$; (ii) when $h=1$, the ET-PF system can achieve robust social welfare optimization without any conditions for Model i , for $i \in (PP, DP)$; (iii) when $h \in (0, 1)$, the RSF service contract is a robust systems optimization policy when $\gamma = \gamma_{SW}^{i*}$

and $\frac{\Omega_{PF}^{SW}}{1-h} - \Omega_{PF}^{i,SW*} \leq \xi_{SW}^i \leq \Omega_{ET}^{i,SW*} - \frac{\Omega_{ET}^{SW}}{1-h}$ hold under Models PP and DP.

Proposition 4.5 shows that different special cases exist. In particular, it is interesting to note that the ET-PF system can naturally achieve robust social welfare systems optimization when $h = 1$ under Model i , for $i \in (PP, DP)$. The reason behind this is: Consumers get the same value either under Model PP or Model DP, and the social welfare is equal to consumer surplus when h is equal to 1.

4.5.3 Endogenous Pricing and Product Quality

In Chapter 4.2, we focus on the product pricing decision for the e-tailer. However, in general, the e-tailer may also have other decisions. In this sub-chapter, we consider the scenario in which the e-tailer makes both the product quality and product pricing decisions.

To be specific, in the e-tailer's business operations, by imposing a better quality control mechanism, the product quality q can be improved with a certain cost. This cost can be related to the equipment upgrades and employing more workers. Hence, we introduce $C(q) = \sigma q^2 / 2$ to capture the cost for quality improvement, it is quadratic which is the common form of the cost function for quality (see, e.g., Yoo and Cheong 2018; Heydari et al. 2017). This quadratic form also indicates that the cost is increasing convex in quality level. Moreover, σ represents the co-efficiency of the investment cost, and $\sigma > 0$. We follow the logic in Chapter 4.2 and present the revised models. To enhance presentation, we add "Q" in front of the model name and hence we have Model QDO, Model QPP, and Model QDP, respectively for the case when the e-tailer sells directly-online, purely through e-platform, and both directly online and through e-platform.

Under Model QDO, the demand function is given by $\hat{d}_{DO} = a - bp + fq$, where q is scaled to have a coefficient of f . It is easy to find that the e-tailer's profit function is given as follows:

$$\Pi_{ET}^{QDO}(p, q) = (p - w - y)(a - bp + fq) - Z - C(q). \quad (4.27)$$

Checking the structural properties shows that $\Pi_{ET}^{QDO}(p, q)$ is concave in p and q (see Appendix (I-6)) if σ is sufficiently large (i.e., $\sigma > f^2 / (2b)$) which makes quality improvement an expensive investment (or else the e-tailer will set q to its upper limit which is less meaningful and interesting to explore). Maximizing $\Pi_{ET}^{QDO}(p, q)$ yields the optimal selling price and product quality level:

$$p_{ET}^{QDO*} = (w + y) + \frac{\sigma(a - b(w + y))}{2\sigma b - f^2} \quad q_{ET}^{QDO*} = \frac{f(a - b(w + y))}{2\sigma b - f^2}.$$

Next, we consider Model QPP in which the e-tailer gives up its own direct-online sales channel and only sells via the e-platform. Under Model QPP, demand is given by $\hat{d}_{PP} = \alpha - \beta p + q$, where q is scaled to have a coefficient of 1 to make the analysis simpler. The e-tailer's profit function under Model PP is given below:

$$\Pi_{ET}^{QPP} = (\phi p - w)(\alpha - \beta p + q) - \xi - C(q). \quad (4.28)$$

Furthermore, the e-platform's profit function under Model QPP is:

$$\Pi_{PF}^{QPP} = (\gamma p - c)(\alpha - \beta p + q) + \xi. \quad (4.29)$$

Summing up (6.33) and (6.34) together yields the total ET-PF system's benefit under Model QPP:

$$\Pi_{SYS}^{QPP} = \Pi_{ET}^{QPP} + \Pi_{PF}^{QPP}. \quad (4.30)$$

Checking the structural properties clearly shows that Π_{ET}^{OPP} and Π_{SYS}^{OPP} are both concave in p and q if σ is sufficiently large (i.e., $\sigma > \phi / (2\beta)$ for all $\phi \leq 1$, which means $\sigma > 1 / (2\beta)$). Maximizing Π_{ET}^{OPP} and Π_{SYS}^{OPP} yields the optimal selling prices and product qualities for the e-tailer and ET-PF

$$\text{system under Model QPP, respectively, } p_{ET}^{OPP*} = \frac{w}{\phi} + \left(\frac{\sigma}{\phi} \right) \left(\frac{\phi\alpha - w\beta}{2\sigma\beta - \phi} \right), \quad q_{ET}^{OPP*} = \frac{\phi\alpha - w\beta}{2\sigma\beta - \phi},$$

$$p_{SYS}^{OPP*} = (w+c) + \left(\frac{\sigma(\alpha - (w+c)\beta)}{2\sigma\beta - 1} \right), \text{ and } q_{ET}^{OPP*} = \frac{\alpha - (w+c)\beta}{2\sigma\beta - 1}.$$

Finally, we have Model QDP which denotes the scenario in which the e-tailer sells its product through both the direct-online sales channel and the e-platform. The demand function is given below:

$$\hat{d}_{DP} = \{a - bp + fq + \lambda(\alpha - \beta p + q)\} + \{\alpha - \beta p + q + l(a - bp + fq)\}. \quad (4.31)$$

Under Model QDP, the profit functions of e-tailer, e-platform, and the ET-PF system are shown below:

$$\Pi_{ET}^{QDP} = \{(p - w - y)(a - bp + fq + \lambda(\alpha - \beta p + q) - Z)\} + \{(\phi p - w)(\alpha - \beta p + q + l(a - bp + fq)) - \xi\} - C(q), \quad (4.32)$$

$$\Pi_{PF}^{QDP} = (\gamma p - c)(\alpha - \beta p + q + l(a - bp + fq)) + \xi, \quad (4.33)$$

$$\Pi_{SYS}^{DP} = \Pi_{ET}^{QDP} + \Pi_{PF}^{QDP}. \quad (4.34)$$

For the notational purpose, we define $E = 2[(\beta + lb)\phi + b + \lambda\beta]$,

$$D = (w + y)(b + \lambda\beta) + w(\beta + lb) + \alpha(\lambda + \phi) + a(1 + l\phi) \quad , \quad F = f + \lambda + \phi(1 + lf) \quad ,$$

$$G = \frac{\lambda(w + y) + w(1 + f + lf) + fy}{f + \lambda + \phi(1 + lf)}, \quad E_{SYS} = 2[\beta + lb + b + \lambda\beta], \quad F_{SYS} = f + \lambda + 1 + lf ,$$

$$D_{SYS} = (w + y)(b + \lambda\beta) + a(1 + l) + \alpha(1 + \lambda) + (w + c)(\beta + lb), \text{ and}$$

$$G_{SYS} = \frac{\lambda(w + y) + (w + c)(1 + lf) + f(w + y)}{f + \lambda + 1 + lf}.$$

Both Π_{ET}^{PP} and Π_{SYS}^{PP} are both concave in p and q if σ is sufficiently large (see Appendix (II-A)). Maximizing them by solving the corresponding first-order-conditions yields the optimal product qualities and selling prices for the e-tailer and ET-PF system under Model QDP, respectively,

$$q_{ET}^{QDP*} = \frac{F(EG - D)}{F^2 - E\sigma}, \quad p_{ET}^{QDP*} = \frac{\sigma q_{ET}^{QDP*}}{F} + G, \text{ and } q_{SYS}^{QDP*} = \frac{F_{SYS}(E_{SYS}G_{SYS} - D_{SYS})}{F_{SYS}^2 - E_{SYS}\sigma}, \quad p_{SYS}^{QDP*} = \frac{\sigma q_{SYS}^{QDP*}}{F_{SYS}} + G_{SYS}.$$

To achieve robust systems optimization in the presence of both product quality and product pricing decisions, it is obvious that we need “one more control variable” as we need to equalize two decisions. Thus, we introduce the cost-sharing scheme into the RSF contract to create the cost-sharing-RSF (i.e.,

CS-RSF) contract as defined below. Under the CS-RSF contract, the e-platform helps the e-tailer with product quality inspection and shares part of the cost. To be specific, the CS-RSF will share $\varepsilon C(q)$ and the e-tailer only needs to pay a product quality cost of $(1-\varepsilon)C(q)$. In the presence of the CS-RSF contract, the optimal decisions of the e-tailer under Model QPP and QDP are revised as follows:

$$p_{ET,CS}^{OPP*} = \frac{w}{\phi} + \left(\frac{(1-\varepsilon)\sigma}{\phi} \right) \left(\frac{\phi\alpha - w\beta}{2(1-\varepsilon)\sigma\beta - \phi} \right), \quad q_{ET,CS}^{OPP*} = \frac{\phi\alpha - w\beta}{2(1-\varepsilon)\sigma\beta - \phi}, \quad q_{ET,CS}^{QDP*} = \frac{F(EG - D)}{F^2 - E(1-\varepsilon)\sigma}, \text{ and}$$

$$p_{ET,CS}^{QDP*} = \frac{(1-\varepsilon)\sigma q_{ET,CS}^{QDP*}}{F} + G.$$

As the cost-sharing is just an internal credit transfer within the ET-PF system, the optimal decisions for the whole system are not affected. We have Proposition 4.6.

Proposition 4.6. *If the e-tailer makes decisions on both the retail product price and product quality: (a) The RSF service contract will fail to achieve robust systems optimization contract under both Model i , for $i \in (PP, DP)$. (b) A product quality cost sharing plus RSF contract, denoted by CS-RSF contract, can achieve ET-PF systems optimization under Model i , for $i \in (PP, DP)$.*

Proposition 4.6 shows that when both product quality and product retail pricing decisions are considered, the RSF alone is insufficient to achieve robust systems optimization. We need the help of the CS-RSF contract to serve, which requires a deeper collaboration between the e-tailer and e-platform.

After having CS-RSF, then an algorithm similar to Algorithm 1 can be developed with the same steps. The only differences include: Replace the RSF contract by the CS-RSF contract. The optimal decisions include product quality and product pricing. The other logics and mechanism of Algorithm 1 all remain valid.

4.6. Summary of this Chapter

Motivated by the observed industrial practices in modern e-tailing, in this work, we have analytically explored the e-tailer's use of e-platform as well as optimal service contracting. First, we have shown analytically how the commonly-seen and widely-adopted revenue-sharing-fixed-fee (RSF) service fee contract can help maximize the e-tailer e-platform (ET-PF) system in the basic model when only pricing is the decision. Second, we have built and examined three models, namely the (pure) direct-online (DO) sales channel, the pure e-platform (PP) sales channel, and the dual direct-online and e-platform (DP) sales channel. For each model, we have derived the optimal pricing decision. Third, we have developed an algorithm, Algorithm 1, which helps achieve robust systems optimization. Finally, we have tested robustness of the results by examining three extensions. For the extension in which the

product is produced by a separate manufacturer and then supplied to the e-tailer, we have uncovered that as long as a suitable supply contract is implemented to achieve “internal coordination” of the product supply chain, all the findings in the basic models remain valid. For the extension which considers the consumer surplus and social welfare optimization objective, we find that the RSF service contract can achieve the ET-PF system coordination. For the extension when the e-tailer considers both product quality and retail product pricing decisions, we have derived the optimal pricing and product quality decisions. We have also uncovered that the RSF service contract fails to achieve robust systems optimization. As a remedial solution, we have proposed the use of a cost-sharing RSF (CS-RSF) service contract to help and proven the efficiency of it. In the following, we discuss the managerial insights and practical implications that we can derive from this study.

The RSF contract: The RSF service contract is a widely used contract in practice. It is encouraging to note that it can yield robust systems optimization under both Model PP and Model DP under the basic model. Thus, when the e-tailer only makes the retail pricing decision, it is optimal for the e-platform to offer the RSF contract which not only maximizes its own benefit, but also maximizes the ET-PF system’s profit. This finding hence supports many industrial practices in which the e-platform charges a fixed fee from the e-tailer as well as shares the revenue generated from each product sold because this is indeed optimal. Moreover, there exists a unique revenue sharing rate with which the e-tailer will price the product at a level the same as the optimal price for the ET-PF system. So, the fixed fee becomes critical to divide the maximized systems profit between the e-platform and the e-tailer. Given that the RSF contract is well-explored in the literature and commonly seen in practice, the findings of its power of achieving robust systems optimization (for the case when the e-tailer only makes the product retail pricing decision) is a piece of good news to the e-tailers. However, it is not perfect if we consider both pricing and product quality as the decisions in the service system.

Whether to use e-platforms: For the e-tailer, whether to use the e-platform can be judged from the systems perspective (see Algorithm 1 and Proposition 4.2). This is a very important finding because this not only means the e-tailer can easily implement the needed optimization algorithm (Algorithm 1), but also guarantees that the optimal channel choice decision for the e-tailer is the same as the optimal channel choice decision for the whole ET-PF system. The detailed steps in Algorithm 1 can be viewed and formulated as a decision support tool to assist operations managers of e-tailers to decide whether or not and when to use e-platforms for their business operations in practice.

An upstream manufacturer is present: If the product supply chain includes an upstream manufacturer and an e-tailer, then, the e-tailer must first work with the manufacturer to achieve internal product supply chain coordination. Proposition 4.3 shows that it can be done by the sales rebate contract. In fact, as this is a typical product supply chain, a contract such as profit sharing and two-

part-tariff will all be applicable for this purpose. After this internal coordination is achieved, the e-tailer can follow the same steps in Algorithm 1 to decide whether it is beneficial to adopt e-platform and select the best channel option. For the e-platform, it can also apply the RSF contract to achieve the ET-PF system's optimality. Thus, in practice, no matter whether the product supply chain is basically formed by one member (e.g., e-tailer) or it includes many members, being internally coordinated is the first step. Luckily, this step is in fact easy to complete and many contracts reported in the supply chain management literature can serve this purpose.

Considering the consumer surplus and social welfare: The consumer surplus and social welfare are both important issues for platform operations as companies are now focusing more and more on social responsibility. As a result, we extend the analysis to consider the impact of consumer surplus on optimal channel selection. The conditions under which the optimal choice of the e-tailer is also beneficial to the consumers are identified. To drill deeper, we propose a novel concept called robust social welfare systems optimization, which aims at optimizing both profit and consumer surplus in the system. The respective findings show that the RSF service contract can help the ET-PF system to achieve the robust social welfare systems optimization in which the value of profit and consumers surplus are both considered simultaneously. This is critical to those e-tailers who aim to become socially responsible business operations. The result also shows the performance of the RSF service contract.

Product quality and retail pricing as decisions: If the e-tailer makes decisions on both the retail product price and product quality, the situation is more complex as the RSF service contract alone is insufficient to achieve robust systems optimization under Model QPP and Model QDP. In this situation, the e-platform needs to consider another contract, such as the CS-RSF service contract, which can provide the needed number of contract parameters to help. In practice, this finding implies that “no pain no gain”. In order to achieve the best system, both e-tailers and e-platforms have to seriously consider the adoption of more sophisticated supply chain contracts if they want to make more sophisticated decisions (i.e., consider more than just product retail pricing, but quality).

Chapter 5 Social Media Platform in the Digital Age: Customized Advertising Strategies and Negative Publicity for Luxury Fashion³⁶

5.1 Problem Statement

5.1.1 Research Background

Over the past decade, advertising has changed its format from traditional print advertisements and TV commercials to be digital. This is especially prominent in the luxury industry. McKinsey reported that digital advertising, such as those via social media platforms like Facebook, Twitter, and Instagram, was related to more than 40% of all luxury sales³⁷.

Today, under COVID-19, luxury fashion brands (LFBs) deeply suffer. It is proposed that social media platform (SMP) advertising is a dominating promotion strategy for luxury fashion operations³⁸. Some industrialists even believe that SMP advertising is probably the most promising way to increase sales and revenue. Indeed, SMP advertising has many beauties, which include the ability to offer customized advertisements to different groups of consumers using the data analytics power and intelligent interactive features (e.g., AI chatbots) of the SMP. Luxury fashion brands such as LV, Dior, Estee Lauder, Gucci, and Burberry have all heavily engaged in SMP advertising. For instance, Gucci has launched a customized advertisement series presenting to different groups of consumers on Facebook and Instagram³⁹. However, SMP advertising incurs non-trivial costs, which include the cost for designing multi-types of digital advertisements (e.g., pictures, videos, theme stories, models and designs), costs for the digital platform services, etc. Kering, the owner of Gucci, spent 50% of its digital budget on social media in 2018⁴⁰. LVMH put a huge budget of US \$6.3 billion on marketing and half would go to SMPs. Other big-spending LFBs on SMP advertising include Burberry and Dior. Owing to such high advertising costs, a well-established luxury fashion brand Bottega Veneta suddenly stopped all its presence in SMPs and hence ceased to promote via them. It hence calls for

³⁶ Abbreviations and notation used are only valid for this chapter.

³⁷ <https://www.ventureharbour.com/luxury-brand-digital-marketing/>.

³⁸ <https://www.forbes.com/sites/josephdeacetis/2021/01/18/the-future-of-fashion-apparel-and-luxury-brand-marketing-in-post-corona-times/?sh=ce2821e4a867>.

³⁹ <https://www.facebook.com/business/success/gucci-us>.

⁴⁰ <https://www.leathermag.com/news/newluxury-brands-increase-social-media-spending-7250532>

deeper explorations on how to engage in SMP advertising, especially for the consideration of customized advertising. Based on the industrial observations, we summarize three types of SMP advertising strategies in Table 5.1.

Table 5.1. SMP advertising strategies.

Advertising strategies		Features	Industrial cases
Customized advertising	Polarized market segmentation (PM) scenario	Advertising towards one group (e.g., fashion leaders) of consumers only (and ignoring the other group (e.g., fashion follows)).	Furla, a luxury bag brand, adopted the polarized market segmentation (i.e., PM) when promoting the winter 2019 collection on Instagram. Specifically, the advertising campaigns were targeted to young Japanese women who are interested in luxury and fashion ⁴¹ .
	Non-polarized market segmentation (NPM) scenario	Advertising towards different groups of consumers with customized contents.	Chloe, a French luxury fashion retailer, launched customized advertisements to different types of consumers (i.e., NPM) by cooperating with various fashion Instagram bloggers to post the content ⁴¹ .
Non-customized advertising		Launching unified advertising contents to all consumers.	Chanel, a French luxury fashion brand, invited top Instagram influencers to share the brand advertisements, which helped the brand to reach all Instagram users (i.e., non-customized advertising) ⁴² .

For operations of luxury fashion brands (LFBs), many important features are present, which make them unique. First, consumers in the market who purchase luxury fashion products not only aim to enjoy the functional aspect of the products, but also the conspicuous aspect, i.e., showing “status” (Li 2019). It is well-known that social influences exist in which the purchasing behavior of a consumer is affected by other consumers (Joshi et al. 2009). Despite being intuitive, this is a non-trivial issue. For example, Burberry, a well-established luxury fashion brand famous for its trench coats, once experienced a problem in which snobbish consumers (Lee et al. 2021) who are fashion gurus (called the fashion leader group in this work) found that many “lower-class consumers” (called the fashion follower group) purchasing and wearing Burberry products in the market and hence they stopped buying. This “social influence” seriously threatened Burberry’s business and hence the brand had to

⁴¹ <https://business.instagram.com/success/furla>.

⁴² <https://mediakix.com/blog/instagram-case-studies-top-brands-campaigns-examples/>.

make a wholesale change in its operations and marketing campaigns. Similar cases are reported for brands such as Dior, and others (see Chiu et al. 2018). Second, controversial advertising is common in luxury fashion. Fashion brands such as Yves Saint Laurent, Gucci, Miu Miu, Marc Jacobs, and Calvin Klein, all are reported to have launched controversial advertisements⁴³. One argument is that controversial advertising can get public awareness (Waller 2006) and would create “negative publicity” (Jørgensen 2003). A recent advertising case in November 2018 by the LFB Dolce and Gabbana (D&G) featuring a Chinese model having difficulty in eating Italian pizza and cannoli with chopsticks⁴⁴. This D&G controversial advertisement created protests by some consumers in Asia and they even claimed to stop buying from D&G. Another brand Dior announced a video called “We are land” in 2019 and was immediately criticized for being racism-related. While there are different opinions on controversial advertising which would create “negative publicity”, we commonly see that they appear from time to time, especially in luxury fashion. So, a fundamental question arises, are there some benefits behind these controversial advertisements in luxury fashion? Third, for LFBs, product pricing relates to brand positioning which is more than revenue management. It is well-documented that for many brands, basically the same product selling price is kept for the similar product lines over many seasons. This is also related to the long product creation process for luxury fashion (Kuksov and Wang 2013). For example, this happens for the LFB Yves Saint Laurent in which its new handbag product line called “Muse Two” at that time had the same selling price as the former handbag product lines’ (such as “Majorelle”) (Yoganarasimhan, 2012) selling price. Indeed, the common way to increase sales revenue in luxury fashion is via advertising, rather than pricing. Thus, advertising strategy is the most critical marketing element for LFBs (Chiu et al. 2018). Nowadays, SMP advertising is the most promising means of advertising by major LFBs. With SMP advertising, LFBs can achieve customized marketing by using consumer data which is a critically important feature. Table 5.2 summarizes the features of LFBs.

⁴³ <https://www.crfashionbook.com/fashion/g29327160/controversial-banned-fashion-ads-calvin-klein-tom-ford/>.

⁴⁴ <https://www.forbes.com/sites/isabeltogoh/2019/08/24/luxury-brands-want-to-attract-chinese-consumers-but-why-do-they-keep-getting-it-so-wrong/?sh=437766aa6a6e>.

Table 5.2. Common features of LFB operations.

	Features
Social influences	Social influences exist between different groups of consumers and snobbish behaviors are critical.
Controversial advertising	Commonly seen while the pros and cons for LFBs are under-explored.
Pricing	Relates to brand image and is always fixed (or very stable) for the same/similar product line.
SMP advertising	Trendy and commonly adopted nowadays. Helps achieve customized advertising.

5.1.2 Research Questions and Major Findings

Motivated by the importance of SMP advertising as well as the presence of social influences and controversial advertisements for LFB operations, this work aims to explore the following problems.

1. For SMP advertising, what are the optimal customized advertising levels? When will the use of the controversial advertisement which creates negative publicity be an optimal strategy?
2. When should LFBs select the customized or non-customized advertising strategy? How would the social influences between different consumer groups affect the optimal advertising strategies?
3. How robust are the findings when we generalize the model with the considerations of endogenous price and the advertising budget constraint?

To address the aforementioned research questions, we build analytical models with a monopoly LFB that plans advertisements on SMPs to sell products. The market demand is influenced by the advertising level. To capture social influences, we formulate two groups of consumers: namely fashion leaders and followers in the market. Demands from two groups of consumers are interrelated. Given the effects of advertising and social influences, the LFB decides the optimal advertising level under various advertising strategies. Two advertising strategies, namely the customized advertising strategy and non-customized advertising strategy, are considered regarding if the same advertising level is adopted toward two groups of consumers. Under the customized advertising strategy, we further examine the non-polarized (NPM) and polarized market segmentation (i.e., PM scenario with Tactic TL and Tactic TF). Specifically, under NPM scenario, the LFB advertises toward both fashion leader group and fashion follower group; while the LFB advertises only toward the fashion leader group (called Tactic TL) or fashion follower group (called Tactic TF) but not both under PM scenario. Since

the LFB advertises two groups in the same advertising level under the non-customized advertising strategy, there are no sub scenarios under this strategy.

Comparing optimal decisions and profits among cases, we analytically identify that social influences (e.g., the snobbishness of leaders), fixed costs for planning customized advertising, and coefficient of advertising levels to demand functions are important factors in determining the optimal advertising strategy, publicity scheme (i.e., positive publicity versus negative publicity), and the value of social influences. First, exploring the implementation of customized and non-customized advertising strategies, we find that the non-customized advertising strategy is dominant when the snobbishness level of fashion leaders is sufficiently low. However, when the snobbishness level is sufficiently high, it is optimal for the LFB to implement the customized advertising strategy if the fixed cost for planning customized advertising is sufficiently low. This finding highlights the significant effect of consumers' conspicuous behavior (i.e., social influences) when advertising on SMPs. Second, we interestingly reveal that controversial advertisements (i.e., negative publicity) could be optimal for the LFB in some cases. For example, when the snobbishness level of Group L is relatively high, it is wise to drive away fashion followers by creating negative publicity. Moreover, we find that the negative publicity is more profitable under the customized advertising strategy compared with the non-customized advertising strategy. Third, exploring the scenario without social influences, we reveal that the non-customized advertising strategy is always optimal, which verifies the value of social influences to the customized advertising strategy. Last but not least, we extend our model to cases where (i) retail price is endogenously determined and (ii) budget of advertising campaigns is constrained. We find that the major findings remain valid in these two extensions. Besides, the effects of pricing and the budget constraint have been uncovered as well.

5.2 Basic Model

5.2.1 Model Setting

We consider an LFB, such as Burberry or LV, that plans to launch advertisements on an SMP (e.g., Facebook) to attract consumers to purchase. In the following, we first introduce the analytical model

for consumer demand, then describe the LFB's optimization models. The abbreviations are summarized in Table 5.3.

Table 5.3. Abbreviations.

Abbreviations	Full Forms
Group L	Fashion leader group
Group F	Fashion follower group
LFB	Luxury fashion brand
NPM	Non-polarized market segmentation
PM	Polarized market segmentation
RVCA	Relative value of co-efficient for advertising towards Group L over Group F
SMP	Social media platform
TL	Targeting fashion leader group
TF	Targeting fashion follower group

A. Two Consumer Groups

In the market, we consider the coexistence of two groups of consumers, namely the fashion leader group (Group L) and the fashion follower group (Group F). Mutual social influences between them are present as depicted in Figure 5.1.

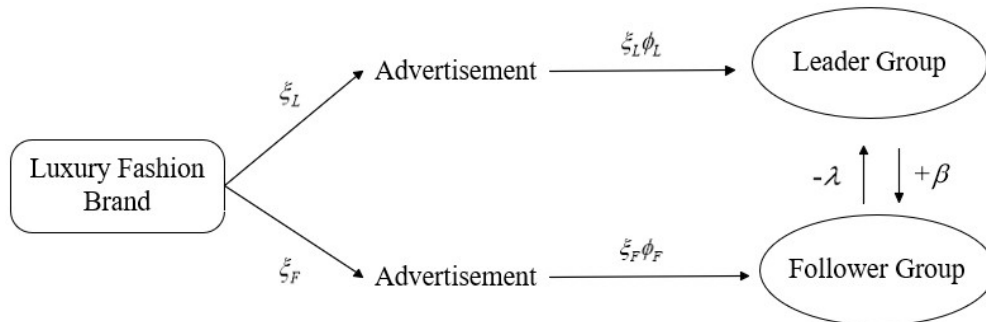


Figure 5.1. Social influences between the two consumer groups on the SMP advertising.

To be specific, Group L includes consumers who are fashion-forward and love the sense of being superior to others. If they buy the luxury product more, the consumers in Group F will be influenced to buy more. On the contrary, if more consumers from Group F buy the luxury product, there will be a negative impact on the Group L consumers because the fashion leaders pursue product exclusivity and behave snobbishly. This phenomenon has been observed in practice (such as the case of Burberry) and also discussed in the literature (see, e.g., Hartl et al. 2003; Amaldoss and Jain 2015; Chiu et al. 2018). To model the above-mentioned social influences, we include two co-efficients in the demand model. Specifically, $\beta \geq 0$ measures the degree of desire that fashion followers follow fashion leaders; $\lambda \geq 0$ measures the level of snobbishness, which represents the degree that fashion leaders enjoy

product exclusivity (Amaldoss and Jain 2015; Lee et al. 2021). The LFB can affect demand by advertising. Regarding the consumer group $i \in \{F, L\}$, the LFB decides the advertising level ξ_i . Note that we allow ξ_i to be positive as well as negative. A positive ξ_i means a traditional demand-enhancing promotional advertisement (Amaldoss and He 2010; Amaldoss and Jain 2015). A negative ξ_i represents the tricky case such as featuring some controversial advertisements or intentionally putting some features in the advertisement to drive away consumers in the group $i \in \{F, L\}$ (Berger et al. 2010); we call it negative publicity in this work. To quantify the advertising effect, we add $\phi_i \xi_i$ to the demand, where $\phi_i \in [0, 1]$ is a co-efficient to scale the effect of advertising level ξ_i . The effects of advertising level are differential depending on consumer types. Note that the LFB advertises and sells the product to two groups of consumers at the same time (e.g., it is a single-period problem), which follows the common practice in luxury fashion in which the new season products are sold to everybody (i.e., including Group L and Group F consumers) in the market. Therefore, we construct the demand model as follows:

$$\begin{cases} D_L = 1 - p + \phi_L \xi_L - \lambda D_F, \\ D_F = n - p + \phi_F \xi_F + \beta D_L, \end{cases} \quad (5.1)$$

where $n > 0$ denotes the market size of Group F. Specifically, we do not restrict $n > 1$ to make our model universal (Amaldoss and Jain 2008, 2015).

From (5.1), we can easily derive the demand for each group of consumers as (5.2) in the following:

$$\begin{cases} D_L = \frac{1 - p(1 - \lambda) - n\lambda + \phi_L \xi_L - \lambda \phi_F \xi_F}{1 + \beta\lambda}, \\ D_F = \frac{n + \beta - p(1 + \beta) + \beta \phi_L \xi_L + \phi_F \xi_F}{1 + \beta\lambda}. \end{cases} \quad (5.2)$$

To enhance exposition, we put the list of notations in Table 5.4. From (5.2), it can be found that, when promoted by advertising, the positive (negative) advertising level ξ_L leads to demand-enhancement (decrease) of both groups; however, the positive (negative) advertising level ξ_F leads to demand-decrease (enhancement) of Group L and demand-enhancement (decrease) of Group F.

Table 5.4. Notation.

Notation	Meanings
ξ_i	LFB's advertising effort.
p	The product price.
c	The production cost, $c \in [0, p]$.
ϕ_i	Co-efficient of advertising levels to demand.
n	The market size of fashion followers.
D_i	Product demand of each group.

β	The degree of desire that fashion followers follow fashion leaders.
λ	The snobbishness of fashion leaders.
F_b	The fixed service cost paid by the LFB to the social media platform.
\widehat{F}	The fixed cost for planning the customized advertisements for one group on the social media platform.
k	Co-efficient of the advertising improvement cost.
B	Budget of advertising campaigns.

Remarks: The type of consumer group is denoted by a subscript $i \in [L, F]$, the advertising strategy is denoted by superscript $t \in [NC, C]$, the market segmentation is denoted by $j \in [NPM, PM]$, and the polarized advertising tactic is denoted by a superscript $f \in [TL, TF]$.

B. The LFB

For Group $i \in \{F, L\}$, the LFB advertises on social media platforms with the advertising level ξ_i . Note that in this work, we do not confine ξ_i to be positive. A key area for exploration of this work is in fact whether the LFB has an incentive to advertise to a consumer group with “negative publicity” in mind. Advertising incurs a cost. In our model, we follow Ozga (1960), Sethi (1983), Amaldoss and He (2010), and Hu et al. (2016) to model advertising cost as an increasing convex function $K_i(\xi_i)$ of the advertising level ξ_i . This functional form captures the fact that: (i) A more effective advertisement (i.e., with a higher absolute advertising level) requires a higher quality advertisement and hence cost. (ii) To improve the effectiveness of advertisement, investing more would yield a stronger effect and the marginal cost is also increasing. Supported by the literature mentioned above and real-world physical meaning, we argue that these fit the LFB advertising problem well. On the SMP, such as Facebook, the LFB may be able to differentiate the specific group of consumers and offer them customized advertisements (which can be completely different). Following the literature (Sethi 1983; Jørgensen 2003; Amaldoss and He 2010; Hu et al. 2016), to derive closed-form results as well as make our findings comparable to prior studies, we set $K_i(\xi_i)$ to be a quadratic function $k\xi_i^2/2$ with $k \in (0, 1]$. Note that as the LFB hires the same advertising firm for creating the advertisement, the marginal cost is the same and hence we have one co-efficient “ k ” for the advertisements for both consumer Groups L and F.

In the basic model, the product selling price p is not considered as a decision. There are several reasons. First, pricing in LFBs is not an operational decision. In fact, LFBs commonly implement the

“prestige-pricing” strategy (Vigneron and Johnson 1999; 2004) in which pricing relates to brand positioning and usually sets at a high level (matching the brand tier). Second, the retail price of luxury fashion brands is usually decided before the selling season as well as the time of advertisements (Chiu et al. 2018). For example, in June 2021, Louis Vuitton has announced its pricing of Cruise 2022 products that are represented by cowboy style, which is much earlier than its selling season. Third, it is widely observed that retail prices of luxury fashion products (from the same/similar series) are very stable across seasons (Yoganarasimhan 2012; Arifoğlu et al. 2020). For instance, Gucci launched a new series of products in cooperation with Balenciaga, namely The Hacker Project in 2021. The retail price of the GG Marmont bag in this project is \$2890 that is similar to the price of classical GG Marmont. This situation is also observed in some other LFBs (see Chiu et al. 2018). Fourth, in this work, we focus on exploring the optimal advertising level ξ_i to optimize the LFB’s profit facing two groups of consumers. Including pricing decision dilutes the focus and makes many results analytically untractable. As such, we do not consider pricing in the basic model (even though as a robustness checking case as well as to cover some less commonly seen cases in LFBs, we study the endogenous pricing case in an extended model).

5.2.2 Advertising Strategies

With the consideration of two consumer groups and the social influences between them, we explore two advertising strategies, namely the customized advertising and non-customized advertising strategies below. We use the superscript t to denote the advertising strategy $t \in [NC, C]$.

Customized advertising: From the view of consumers, two consumer groups will experience specialized advertisements for their types under the customized advertising strategy. The coefficients of the advertising effect on the demand for Group L and Group F are considered to be different, which are denoted by ϕ_L and ϕ_F , respectively. On the other hand, if the LFB plans to launch a “specific” customized advertisement for each consumer group, then it needs to pay the basic setup cost for using the SMP to advertise, F_b , and the customized advertising service cost, $F_c(x)$, that includes the extra fixed advertising fee associated with the customized advertising service such as the SMP helping the LFB strategically advertises to the specified groups, where x is the number of consumer groups being

targeted at. That is to say, the cost of customized advertising service is determined by the number of consumer groups, and the cost of targeting a single group is \widehat{F} . Specifically, the customized advertising service cost $F_c(x) = 2\widehat{F}$ when the LFB targets both Group L and Group F; while $F_c(x) = \widehat{F}$ when the LFB targets one of the two groups⁴⁵. Based on the model settings, the LFB decides the optimal advertising levels ξ_L and ξ_F to maximize its profit. The optimization problem for the customized advertising scenario can be obtained as (5.3).

$$\max_{\xi_L, \xi_F} \Pi^C(\xi_L, \xi_F) = (p - c)(D_L + D_F) - F_b - F_c(x) - \frac{k\xi_L^2}{2} - \frac{k\xi_F^2}{2}. \quad (5.3)$$

Non-customized advertising. From the perspective of consumers, irrespective of whether they are from Group L or Group F, they will be shown the same common advertisement offered by the LFB on the SMP under the non-customized advertising strategy. We denote the common non-customized advertising level as ξ . Similar to the customized advertising case, coefficients of the advertising effect are given by ϕ_L and ϕ_F considering the consumer types. Putting $\xi_L = \xi_F = \xi$ into (5.2), the demands for two groups of consumers under non-customized advertising scenario can be obtained in the following:

$$\begin{cases} D_L^{NC} = \frac{1 - p(1 - \lambda) - n\lambda + \xi\phi_L - \lambda\xi\phi_F}{1 + \beta\lambda}, \\ D_F^{NC} = \frac{n + \beta - p(1 + \beta) + \beta\xi\phi_L + \xi\phi_F}{1 + \beta\lambda}. \end{cases} \quad (5.4)$$

From the perspective of the firm, the LFB plans a common non-customized advertisement for both groups of consumers. It needs to pay only the fixed setup cost F_b to the SMP for the advertisement service but not the customized advertising service cost $F_c(x)$. Therefore, the LFB determines the optimal common advertising level to maximize the profit that consists of the income from product selling and advertising cost. The optimization problem is provided in (5.5):

$$\max_{\xi} \Pi^{NC}(\xi) = (p - c)(D_L^{NC} + D_F^{NC}) - F_b - \frac{k\xi^2}{2}. \quad (5.5)$$

⁴⁵ Note that we consider the customized advertising cost is a fixed that increases in the number of consumer groups instead of the demand of consumers as the focal point of this study is to uncover the significance of social influences on optimal advertising levels. Therefore, the current setting of fixed customized advertising service cost can not only avoid the trivial solutions but also is useful to uncover major findings clearly.

Solving (5.5), we derive the optimal advertising level is $\xi^{NC*} = \frac{(p-c)((1+\beta)\phi_L + (1-\lambda)\phi_F)}{k(1+\beta\lambda)}$.

5.3 Analysis

5.3.1 Customized Advertising Strategy

We first explore the customized advertising strategy, in which each consumer group receives a customized specific advertisement. Considering the customized service cost to target one group and the advertising effect, whether or not to advertise towards two groups together is crucial for the LFB (Chui et al. 2018). Therefore, under the customized advertising strategy, we consider two scenarios of market segmentation regarding whether the LFB should advertise towards the two consumer groups simultaneously, namely the non-polarized market segmentation (NPM) scenario and polarized market segmentation (PM) scenario (as depicted in Figure 5.2). Intuitively, the NPM scenario means that the LFB advertises towards both groups with specific advertisements, and the firm undertakes the customized advertising cost $F_c(x) = 2\widehat{F}$. However, the PM scenario means that the LFB targets only one of the two groups and gives up advertising towards the other group (i.e., the advertising level is zero), and the customized advertising cost goes down to $F_c(x) = \widehat{F}$. Thus, under PM, the advertising level for one group of consumers equals zero; for example, under Tactic TL (*resp.* Tactic TF), only Group L (*resp.* Group F) is targeted and $\xi_F = 0$ (*resp.* $\xi_L = 0$). Solving (5.3), it is interesting to find that under both NPM and PM scenarios the optimal advertising levels for the targeted groups can be obtained as $\xi_L^* = \frac{(p-c)(1+\beta)\phi_L}{k+k\beta\lambda}$ and $\xi_F^* = \frac{(p-c)(1-\lambda)\phi_F}{k+k\beta\lambda}$, and one of them will be zero under PM. From them, it can be uncovered that the optimal advertising levels for the targeted groups are affected by the social influences including the snobbishness of Group L (i.e., λ) and the degree of desire (i.e., β) that Group F follows Group L. To be specific, when Group L is more snobbish, the optimal advertising level towards this group should drop (if it is not zero for the PM scenario); similarly, the optimal advertising level towards Group F (if it is not zero for the PM scenario) should decrease if this group becomes more desirable to follow Group L. That is to say, the optimal advertising level towards the specific group decreases in this group's social influence.

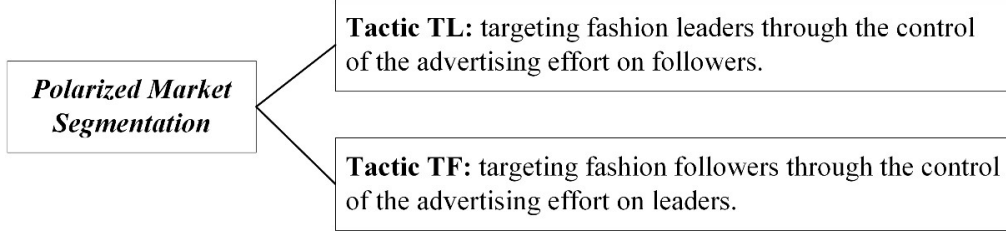


Figure 5.2. PM scenario under the customized advertising strategy.

Next, we explore the optimal advertising tactic under the PM scenario. As discussed, the PM scenario includes Tactic TL and Tactic TF with different targeted group. To understand the effect of social influences on the optimal tactic of PM scenario, we compare profits between Tactic TL and Tactic TF and define the difference $\Delta\Pi^{C-f} = \Pi^{C-TL} - \Pi^{C-TF}$, where $f \in [TL, TF]$. We have Proposition 5.1.

Proposition 5.1. (optimal advertising tactic under the PM scenario) *The LFB should select Tactic*

TL (resp. Tactic TF) if and only if $\frac{\phi_L}{\phi_F} > \left| \frac{1-\lambda}{1+\beta} \right|$ (resp. $\frac{\phi_L}{\phi_F} < \left| \frac{1-\lambda}{1+\beta} \right|$).

Proposition 5.1 proposes that the LFB should adopt Tactic TL (i.e., $\Delta\Pi^{C-f} > 0$) when ϕ_L/ϕ_F , termed as the “*relative value of coefficient for advertising towards Group L over Group F*” (RVCA), is larger than $\left| \frac{1-\lambda}{1+\beta} \right|$. This relative value measures the sensitivity of Group L over Group F to advertisements, a higher value implies Group L is more sensitive to advertisements (relative to Group F’s sensitivity). Therefore, the main reason for the finding in Proposition 5.1 is that when advertising towards Group L is more effective to attract consumers, implementing Tactic TL is more profitable. Moreover, it can be observed that the adoption of polarized tactics is significantly affected by social influences (i.e., evaluated by λ and β). Interesting findings can be uncovered related to the snobbishness level of Group L. To be specific, we find that when the snobbishness level of the fashion leader is low, that is λ is relatively small (i.e., $0 < \lambda \leq 1$), the LFB is more inclined to target Group L if λ increases. However, when the snobbishness level of the fashion leader is high, which means a larger λ (i.e., $\lambda > 1$), it is more attractive for the LFB to target Group F if λ increases. That is to say, the effect of Group L’s snobbishness on the optimal advertising tactic varies for different levels of snobbishness. This interesting phenomenon appears because of the adoption of negative publicity. To

be exact, owing to the social influences, Group L becomes decreasingly enticed to purchase this luxury fashion product when more Group F consumers enter the market, and this negative effect is stronger with a higher snobbishness level (i.e., a higher λ). Therefore, intuitively, when λ is increasing, it is optimal for the LFB to give up advertising towards Group F (adopting Tactic TL) in order to avoid the loss of sales from Group L. However, when this negative effect goes very strong, it motivates the LFB to adopt Tactic TF but implement negative publicity on this group aiming to keep more higher-end customers (i.e., Group L). The implementation of negative publicity will be elaborated in Proposition 5.4.

Proposition 5.2. (optimal market segmentation scenario under customized advertising strategy)

Under the customized advertising strategy, the LFB should present PM Scenario with TL if $\widehat{F} > \widehat{F}_L$ and present with TF if $\widehat{F} > \widehat{F}_F$; otherwise, the LFB should present NPM Scenario. (Thresholds used in propositions and lemmas are provided in Appendix II-C.)

Proposition 5.2 shows that the optimal customized advertising market segmentation is significantly affected by the customized advertising fixed cost paid to the SMP \widehat{F} (Iyer et al. 2005). Specifically, facing the relatively high fixed cost for targeting consumers (i.e., higher \widehat{F}), the PM scenario is more cost-efficient. Moreover, observing the thresholds of \widehat{F} (i.e., \widehat{F}_L and \widehat{F}_F), we interestingly find that the thresholds are evaluated by the term $T = \frac{(p-c)^2}{2k(1+\beta\lambda)^2}$ which we call “*scaled profitability of advertising under social influences*”. This term captures the proportion of marginal cost $(p-c)$ and marginal advertising cost under social influences. Thresholds of \widehat{F} (i.e., \widehat{F}_L and \widehat{F}_F) increase in term T . Therefore, $\widehat{F} > \max\{\widehat{F}_L, \widehat{F}_F\}$ can be elaborated deeply as the fixed cost for customized advertising is larger than the scaled profitability of advertising under social influences. The threshold of \widehat{F} increase in T , which means that the LFB becomes more willing to present the NPM scenario with the higher scaled profitability of advertising under social influences.

5.3.2 Comparisons Between Customized and Non-customized Advertising Strategies

In Chapter 5.3, we uncover the optimal implementation of the customized advertising strategy, including the adoption of polarized tactics and presentation of market segmentation. In this part, we explore the optimal advertising strategy by comparing the customized and non-customized advertising strategies.

Proposition 5.3. (optimal advertising strategy) *The customized advertising strategy (i.e., the NPM scenario, Tactic TL, and Tactic TF) is optimal for the LFB if only if $\lambda > 1$ and $\widehat{F} < \max\{\widehat{F}_2, \widehat{F}_3\}$. Otherwise, the non-customized advertising strategy is optimal for the LFB.*

Proposition 5.3. uncovers that the customized advertising strategy is not always optimal for the LFB. It is suggested to consider the social influences (especially for the snobbishness of Group L) and the fixed cost for planning customized advertising when making an advertising strategy. Specifically, we find that when Group L is more snobbish, the LFB to be more inclined to advertise toward two groups of consumers with diverse contents. Customized advertising helps the LFB maximize its profitability from Group L by reducing the defection of this type of consumer. The main reason is the implementation of negative publicity, which will be discussed in Proposition 5.4. Note that, this finding is different from the finding of Amaldoss and Jain (2015) to some extent. In Amaldoss and Jain (2015), the authors find that the firm, which sells products to high-end and low-end consumers, is better off using the same brand name instead of different brand names when the snobbishness is higher. Even though the operation strategy explored in this work: customized and non-customized advertising differs from branding strategy in Amaldoss and Jain (2015). Advertising and branding strategy are both related to a firm's marketing strategy. Therefore, this work uncovers a finding that is opposite to Amaldoss and Jain (2015): it is optimal for the LFB to advertise toward different two groups of consumers with diverse advertisements (marketing strategy) when the fashion leader consumers (high-level consumers in Amaldoss and Jain (2015)) are more snobbish.

Moreover, from the perspective of cost-efficiency, the LFB should pay attention to the fixed cost of customized advertising when making the optimal advertising strategy. Only when the snobbish level of Group L is relatively high and the customized service cost is relatively low, customized advertising is the optimal choice.

Summarizing findings in Propositions 5.1-3, we provide Figure 5.3 that visualizes the overall optimal advertising strategy with respect to the effects of snobbishness (i.e., λ) and the fixed cost of customized advertising. To be exact, when consumers are less snobbish (i.e., $\lambda < 1$), customized advertising will never be the optimal strategy. Besides, facing the higher snobbish level (i.e., $\lambda > 1$), with the increased fixed cost of customized advertising, the optimal adoption of advertising strategy for the LFB changes from the NPM scenario, PM scenario, to the non-customized advertising strategy; Moreover, if the fixed cost of customized advertising is moderate, the adoption of tactic depends on the value of snobbish level. The detailed expressions are provided in Appendix II-C.

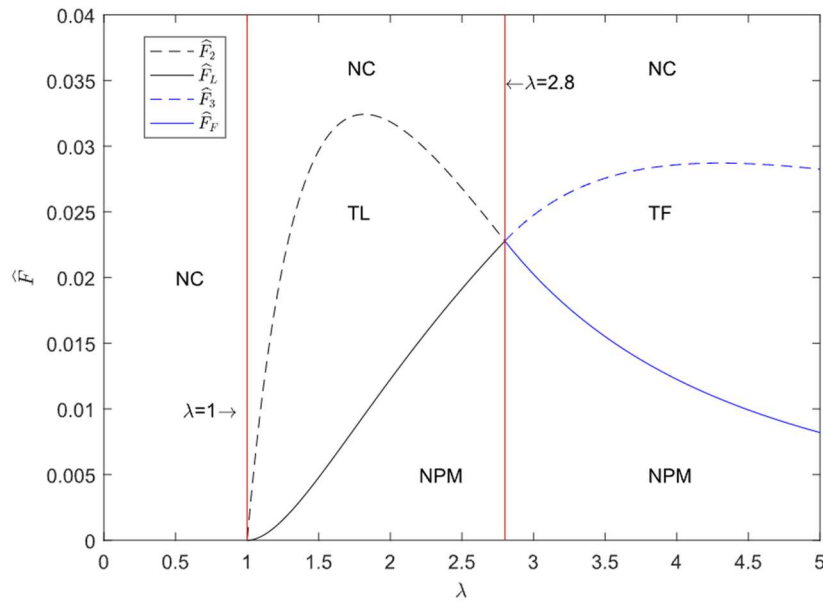


Figure 5.3. The optimal advertising strategy ⁴⁶ ($p=0.8$, $\beta=2$, $c=0.1$, $\phi_L=0.3$, $\phi_F=0.5$, and $k=0.2$).

5.3.3 Value of Negative Publicity

If we look at the market segments, conventional wisdom may propose that it is unwise for the LFB to target the follower group consumers, who are usually the lower-end consumers and cannot bring much profit for the luxury company. However, according to the exploration on optimal advertising levels, we interestingly find that it is not necessarily the case. In fact, the implementation of negative publicity

⁴⁶ Remarks: In Figure 5.3, the NC region refers to the case in which the non-customized advertising strategy is optimal. The TL, TF, and NPM regions respectively show the optimal advertising strategy for the cases with Tactic TL, Tactic TF, and the non-polarized market segmentation scenario of the customized advertising strategy.

is the key reason which supports the “counter-intuitive” proposal of targeting the followers' group. We have Proposition 5.4.

Proposition 5.4. (positive publicity or negative publicity) (i) Under the customized advertising strategy, it is always optimal for the LFB to implement the positive publicity scheme for Group L, while negative (positive) publicity scheme for Group F when $\lambda > 1$ ($\lambda < 1$). (ii) Under the non-customized advertising strategy, it is optimal for the LFB to implement the negative (positive) publicity scheme for both groups when $\lambda > 1 + \frac{(1 + \beta)\phi_L}{\phi_F}$ ($\lambda < 1 + \frac{(1 + \beta)\phi_L}{\phi_F}$).

Proposition 5.4 is crucial and it uncovers when it is optimal for the LFB to implement positive or negative publicity via advertisements. We interestingly find that the implementation of positive or negative publicity depends on the advertising strategy and consumer type. To be specific, under the customized advertising strategy, it would be optimal for the LFB to implement the negative (positive) publicity scheme for Group F (L) no matter for the NPM and PM scenarios. By contrast, under the non-customized advertising strategy, the LFB advertises towards two groups with the uniform attribute of publicity, in which the negative publicity would be optimal for them (when λ is high enough). The main reason for having such optimal implementation of publicity is due to the effects of social influences. In this study, social influences refer to the behavior that Group L stimulates the desire of Group F to purchase the product in order to obtain a higher social status (Mauss 2002), while Group F's purchases will reduce demand from Group L. With these influences, if the customized advertising is implemented, it is logical that the LFB should always implement positive publicity for Group L to increase the corresponding demand and attract more Group F at the same time. However, the positivity or negativity of optimal advertising level towards Group F depends on the degree of social influences. Specifically, when Group L is more snobbish (i.e., λ is relatively high), the LFB should give up Group F and implement the negative publicity to drive them out. Consequently, it significantly attracts the attention of Group L, which helps the LFB to obtain a higher profit. Such a finding can demonstrate the reason for the sales up of D&G in 2019 after its advertising controversy. As shown by statistics, Asia market consumers are not the mainstream consumers of luxury products compared with consumers from America and Europe⁴⁷. In the D&G advertising controversy, Asia market consumers

⁴⁷ https://media.bain.com/Images/BAIN_REPORT_Global_Luxury_Report_2017.pdf.

who felt bad towards the controversial advertisement left, but the public awareness had attracted more American and European consumers in the market to purchase, which eventually resulted in the sales up of D&G in 2019. On the other hand, if the non-customized advertising strategy is implemented, social influences form the implementation of publicity schemes. Table 5.5 summarizes the characteristics of the optimal advertising levels under each advertising strategy including both NPM and PM scenarios.

Proposition 5.4 reveals that it would be optimal for the LFB to implement the negative publicity scheme on SMP advertising, which is a bit different from our intuition. In practice, the negative publicity, which may imply the controversial advertisement or even “firing” the consumers, has attracted attention in both academia and industry (Berger et al. 2010; Jørgensen 2003; Shin and Sudhir 2013). In Table 5.6, we summarize the meaning of different publicity schemes with examples of them.

Table 5.5. Features of optimal advertising levels.

	NPM		PM	
			TL	TF
	ξ_L	ξ_F	ξ_L	ξ_F
Customized advertising	+	- if $\lambda > 1$; 0 if $\lambda = 1$; + otherwise.	+	- if $\lambda > 1$; 0 if $\lambda = 1$; + otherwise.
Non-customized advertising	- if $\lambda > 1 + \frac{(1+\beta)\phi_L}{\phi_F}$; 0 if $\lambda = 1 + \frac{(1+\beta)\phi_L}{\phi_F}$; + otherwise.			

Table 5.6. Explanations of different advertising levels.

Advertising level	Meaning	Example
+	The LFB implements a positive publicity scheme to enhance purchasing intention.	Positive advertisement about the products or service, such as good quality (Feng and Xie 2012).
0	The LFB does not advertise on the SMP.	Luxury fashion brands stop advertising on SMPs. For example, Bottega Veneta stopped advertising on Instagram.
-	The LFB implements a negative publicity scheme to consumers to discourage purchasing intention.	Controversial advertisements may with the aim of “fire the consumers”, such as fear and racial image (Waller 2006).

According to the overall optimal decision of advertising strategy provided in Proposition 5.3 (e.g., Figure 5.3), the optimal implementation of publicity concerning the snobbishness level of Group L and the fixed cost of customized advertising, which is depicted as Figure 5.4. Several interesting findings can be uncovered. First, we find three patterns of optimal publicity implementation with respect to the positive, negative publicity, and zero decisions towards the two consumer groups. To be specific, the three patterns are “uniform publicity”, “opposite publicity”, and “polarized publicity”. The “uniform publicity” pattern means the optimal advertisements toward two consumer groups are “uniform” that can be both positive or both negative. The “opposite publicity” refers to the pattern in which the advertisement approaches toward the two consumer groups are opposite (i.e., one positive one negative). For “polarized publicity”, the optimal advertisement on one of the two groups equals zero. Second, we uncover that the implementation of publicity patterns depends on \hat{F} and λ (consistent with findings from Proposition 5.3 and Proposition 5.4). To be specific, (i) the “uniform publicity” pattern is induced by a higher fixed cost of customized advertising. When this fixed cost is higher, the LFB should better adopt the non-customized advertising strategy. Moreover, the snobbishness level of Group L further affects the positivity and negativity of the “uniform publicity”. As stated in Proposition 5.4, the LFB should implement positive publicity when Group L is less snobbish, while negative publicity when Group L is strongly snobbish. (ii) The “opposite publicity” pattern is optimal when the fixed cost of customized advertising is lower and the snobbishness level of Group L is relatively higher. This is because the relatively lower fixed cost of customized advertising makes the NPM scenario more profitable for the LFB. This phenomenon leads to the “opposite publicity” pattern to soften the detriment of the snobbishness of Group L when λ is relatively higher. (iii) When the fixed cost of customized advertising for one group is moderate, “polarized publicity” should be applied. Furthermore, in this case, the negative publicity is optimal when the snobbishness level of Group L is relatively higher.

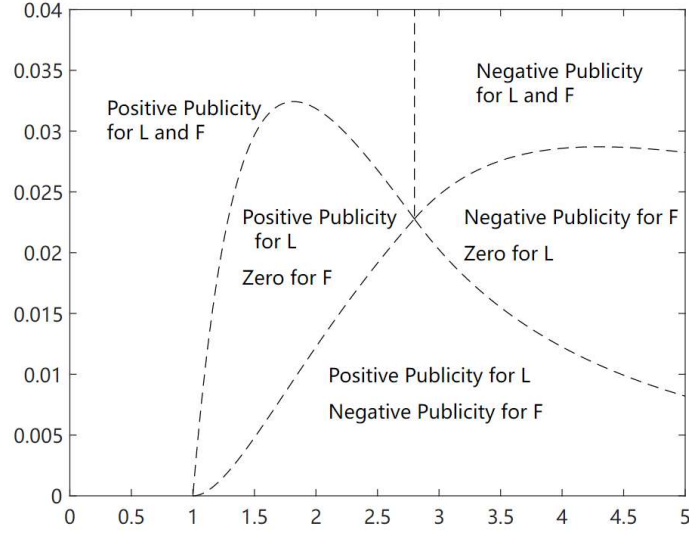


Figure 5.4. The optimal implementation of publicity ($p=0.8$, $\beta=2$, $c=0.1$, $\phi_L=0.3$, $\phi_F=0.5$, and $k=0.2$).

From the above analysis, we identify a critical insight that negative publicity is the key to fighting against the severe negative effect brought by the snobbish behavior of Group L. Exploring the value of negative publicity, we have Proposition 5.5. Note that, $\Delta\Pi_{VN}^{t-j/f}$ is used to denote the differences between the optimal profits and the “profits when the negative advertising levels are equal to zero”, where the superscript j and f are used to denote the market segmentation scenarios, i.e., NPM and PM, and polarized advertising tactics, i.e., Tactic TL and Tactic TF, respectively.

Proposition 5.5. (value of negative publicity) (a) *Values of negative publicity are the same for the NPM and PM scenarios under the customized advertising strategy, i.e., $\Delta\Pi_{VN}^{C-NPM} = \Delta\Pi_{VN}^{C-TF}$.* (b) *The negative publicity is more effective for the customized advertising strategy compared with the non-customized advertising strategy, i.e., $\Delta\Pi_{VN}^{NC} < \Delta\Pi_{VN}^{C-NPM} = \Delta\Pi_{VN}^{C-TF}$.*

From Proposition 5.5(a), first, it is interesting to note that the influence of negative publicity on driving away fashion followers and keeping fashion leaders will not be affected by the market segmentation (i.e., NPM versus PM). Under the NPM and PM scenarios, the LFB only implements negative publicity on Group F with the same marginal advertising cost for this group. Such a reason leads to the same changes of optimal advertising level for these two scenarios. On the other hand, we verify that the negative publicity is more profitable for the customized advertising strategy with the effect of social influences. As discussed in Proposition 5.4, under the customized advertising strategy,

the LFB implements positive publicity for Group L to increase the overall demand; meanwhile, the LFB drives off Group F in order to keep more Group L by implementing negative publicity. In other words, the LFB can optimize profits from fashion leaders and followers in the best way with the help of a customized advertising strategy. By contrast, the non-customized advertising strategy fails to catch up with the profits from two groups of consumers. When launching a common advertisement, if the LFB selects the controversial advertisement towards two groups which means creating negative publicity, it actually reduces the purchasing intention of Group L consumers even though it helps fight against the snobbishness of Group L (by driving off Group F). Therefore, in this case, the negative publicity is less effective to help the LFB to obtain profitability compared with the customized advertising strategy.

5.4 Without Social Influences

In Chapter 5.3, we consider the situation when Group L behaves snobbishly and Group F has a desire to follow Group L. This setting captures the conspicuous behavior of consumers. To conduct a comparison analysis and explore the optimal implementation of advertising strategy without the consideration of consumers' conspicuous behavior, we examine the case without social influences as a benchmark. In this benchmarking case, demands of Group L and Group F can be expressed as $\bar{D}_L = 1 - p + \phi_L \xi_L$ and $\bar{D}_F = n - p + \phi_F \xi_F$ (we denote the case without social influence by using the bar on top of the notation). To maximize its profits, the LFB decides the optimal advertising levels under various advertising strategies. Note that, constitutions of profit functions in this benchmarking case are similar to the case with social influences while replacing the expressions of demand. Solving the corresponding objective functions and comparing them, we have Proposition 5.6.

Proposition 5.6. (Optimal advertising strategy) *Without social influences: (i) Under the customized advertising, the LFB should select Tactic TL (resp. TF) when $\frac{\phi_L}{\phi_F} > 1$ (resp. $\frac{\phi_L}{\phi_F} < 1$), and the PM scenario is superior to NPM scenario when $\hat{F} > \max\left\{\frac{(p-c)^2 \phi_L^2}{2k}, \frac{(p-c)^2 \phi_F^2}{2k}\right\}$. (ii) The non-customized advertising is optimal than the customized advertising strategy (i.e., the NPM scenario, PM scenario with TL and TF tactics).*

Proposition 5.6 shows the optimal advertising strategy when social influences are absent (i.e., $\beta = 0$ and $\lambda = 0$). Consistent with the investigations in Proposition 5.1 and 5.2, we find that the optimal adoption of market segmentation under customized advertising strategy depends on the fixed cost of customized advertising and the ratio $\frac{\phi_L}{\phi_F}$. The LFB should present PM (i.e., TL and TF) when \hat{F} is sufficiently large; in this case, TL (TF) is more preferable if Group L (F) is more sensitive to advertisements. On the other hand, we find that non-customized advertising is always being dominated compared with scenarios of customized advertising strategy. The main reason is that customized advertising fails to alleviate the cost of customization for the case without the social influences. Proposition 5.6 (ii) is to some extent consistent with our finding in Proposition 5.3 that the non-customized advertising strategy will always be optimal when $\lambda < 1$. This finding implies that the customized advertising strategy is costly and inferior to the non-customized strategy without the consideration of social influences. That is to say, it is optimal for less-luxury products (e.g., fast fashion products), which target consumers who show non-obvious social influences, to plan non-customized advertising. Findings in Proposition 5.6 thus demonstrate that the customized advertising strategy is crucial for the LFB to respond to consumers' conspicuous consumption.

In order to further explore how the social influences play a role in uncovering the value of customized advertising strategy, we numerically study the trends of differences for profits between cases with and without social influences with respect to β (i.e., the degree of desire that fashion followers follow fashion leaders). Findings are depicted in Figure 5.5. Note that in Figure 5.5, the *Value of Social Influences* represents the profit difference between the cases with and without social influences.

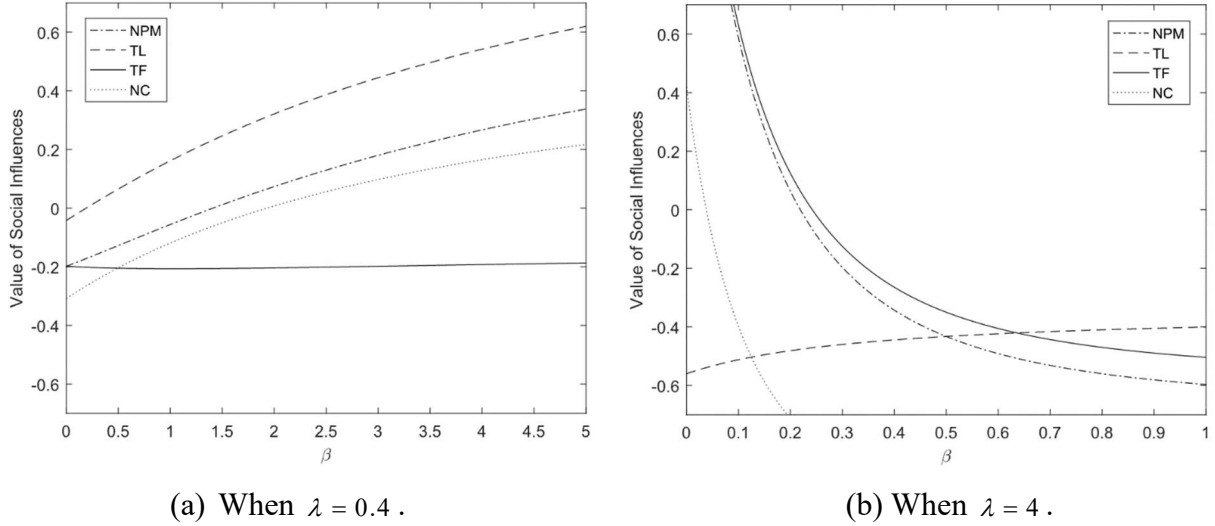


Figure 5.5. Value of social influences ($p=0.8$, $c=0.1$, $\phi_L=0.3$, $\phi_F=0.5$, $k=0.2$, and $n=1$).

From Figure 5.5, we generate several observations regarding the *Value of Social Influences*. First, observing Figure 5.5 (a) and (b), we can find that the *Value of Social Influences* is affected by the snobbishness level. When $\lambda = 0.4$, considering the effect of β will increase the LFB's profitability when adopting the NPM scenario, Tactic TL, and non-customized advertising strategy; while not affecting the LFB's profitability if Tactic TF is adopted. However, when $\lambda = 4$, considering the effect of β may increase the profitability of the LFB when the NPM scenario, Tactic TF, and the non-customized advertising strategy are adopted except for Tactic TF. As discussed in Proposition 5.3, regarding the adoption of PM, it is optimal for the LFB to select Tactic TF when the snobbish level of Group L is relatively higher. Second, we observe that the effects of Group F's degree of desire to follow Group L (i.e., β) on *Value of Social Influences* are distinct for different λ . Specifically, when $\lambda = 0.4$, the *Value of Social Influences* increases in β for cases where social influences play a role. On the contrary, when $\lambda = 4$, the *Value of Social Influences* decreases in β for cases where social influences play a role. The aforementioned opposite phenomenon may be explained by the mutual "two-sided" effects of social influences. When Group L consumers are not too snobbish, the increase of Group F's desire to follow Group L is effective to expand the market by enticing more followers, which is beneficial for the LFB. However, if Group L is sufficiently snobbish, the influx of followers hurts the social status of Group L consumes, which in turn is detrimental for the LFB. Third, we find that considering the effect of social influences is able to improve the profitability for the LFB when

adopting not only the customized advertising strategy but also the non-customized advertising strategy. It uncovers the importance of paying attention to social influences when planning advertising on SMPs.

5.5 Extensions

We extend our explorations in this sub-chapter to test the robustness of our findings in the basic model. Specifically, we examine two extensions which include the cases with (i) an endogenous pricing decision and (ii) the consideration of budget constraints. Through these two extensions, we find that important findings of the basic model remain valid, which demonstrates the robustness of our results.

5.5.1 Endogenous Price

In the basic model, we have considered that the selling price of the luxury fashion product is exogenously given and fixed. This relates to the nature of luxury fashion products, which is well documented in the literature (see Kuksov and Wang 2013; Chiu et al. 2018). However, nowadays, owing to COVID-19 and other changes in the market environment, we have seen some luxury fashion brands also give up their “stable-price tactic” (for holding the brand image) and offer discounts (i.e., change prices) (Arifoğlu et al. 2020). This is especially true for the less luxury fashion brands. Thus, uncovering the interaction between advertising and pricing decisions would be helpful for us to better understand the impacts brought by pricing on SMPs advertising. We hence consider the endogenous pricing case here. Moreover, whether the rule of implementing the optimal advertising strategy remains the same with our basic model will be explored. Note that to focus on uncovering how the LFB should make the optimal advertising strategy affected by the social influences especially for the snobbishness, we consider the case in which the market base of Group F equals that of Group L (i.e., $n=1$).

To allow endogenously determining the optimal price of the luxury fashion product, we modify objective functions for the customized advertising as follows

$$\max_{\xi_L, \xi_F, p} \Pi^C(\xi_L, \xi_F, p) = (p - c)(D_L + D_F) - F_b - F_c(x) - \frac{k\xi_L^2}{2} - \frac{k\xi_F^2}{2}. \quad (5.6)$$

and non-customized advertising as

$$\max_{\xi, p} \Pi^{NC}(\xi, p) = (p - c)(D_L^{NC} + D_F^{NC}) - F_b - \frac{k\xi^2}{2}. \quad (5.7)$$

The LFB simultaneously decides the optimal sales price and advertising levels. Consistent with the basic model, we explore the NPM and PM scenarios for the customized advertising strategy. Solving (5.6) under different market segmentation scenarios and (5.7), we obtain the optimal pricing and advertising levels that are provided in Appendix II-C.

Proposition 5.7. (analysis on the optimal price) (i) Under the customized advertising strategy, the LFB should increase the selling price when ϕ_L or ϕ_F increases. (ii) Under the non-customized advertising strategy: (a) The optimal selling price increases with ϕ_L when λ is sufficiently high or moderate; otherwise, it decreases with ϕ_L ; (b) the optimal selling price increases with ϕ_F when λ is sufficiently high or low; otherwise, it decreases with ϕ_F .

Proposition 5.7 shows the impacts of co-efficients of advertising level to demand on the optimal selling price, which are different for the customized and non-customized advertising strategy. Under the customized advertising strategy, the advertisement differentiation enables the LFB to charge a higher price from consumers if consumers become highly affected by advertisements (i.e., high ϕ_i). Differently, non-customized advertising makes the setting of optimal pricing decision more complex when the demand is highly affected by advertisements. The LFB should make the optimal selling price depending on the consumer types and social influences, especially for Group L's snobbishness level. First, if the snobbishness level of Group L is relatively low or moderate (i.e., $0 < \lambda < \min\{1 + \frac{2(1+\beta)\phi_L}{\phi_F}, 2 + \beta\}$), it is more profitable for the LFB to provide a higher price when the demand of Group L is increasingly affected by advertising. It is because the demand enhancement stimulated by advertisement surpasses the demand decline due to Group L's snobbish behavior. Therefore, the LFB is willing to increase the marginal profit by charging a higher selling price. Second, compared with the effect of ϕ_L on price, an opposite finding is uncovered regarding the effect of ϕ_F on selling price. When the demand of Group F is significantly affected by advertising, the LFB should markdown if Group L's snobbish level is moderate (i.e., $1 < \lambda < \min\{1 + \frac{2(1+\beta)\phi_L}{\phi_F}, 2 + \beta\}$). It is because, when Group L is less snobbish, purchasing from Group F can moderately lead to a demand decline of Group L. In such a case, with an increase ϕ_F , it is effective to attract more consumers by advertising and reducing the price. Findings for the effects of ϕ_i on the optimal pricing decision reflect that the pricing decision and advertising strategy interact with each other, which makes it complicated to

determine the optimal advertising strategy. We have Proposition 5.8 that states the optimal advertising strategy when pricing is the decision.

Proposition 5.8. (optimal advertising strategy) (i) Under the PM scenario, the LFB should select Tactic TL (resp. TF) when $\frac{\phi_L}{\phi_F} > \left| \frac{1-\lambda}{1+\beta} \right|$ (resp. $\frac{\phi_L}{\phi_F} < \left| \frac{1-\lambda}{1+\beta} \right|$). (ii) Comparing the PM and NPM scenarios, the LFB should adopt the PM scenario (i.e., TF or TL) when $\widehat{F} > \max\{\widehat{F}_L^{EP}, \widehat{F}_L^{EP}\}$. (iii) Comparing the customized and non-customized advertising strategies, it is optimal for the LFB to adopt a customized advertising strategy if and only if $\lambda > 1$ and $\widehat{F} < \max\{\widehat{F}_1^{EP}, \widehat{F}_2^{EP}, \widehat{F}_3^{EP}\}$; otherwise, the non-customized advertising strategy is optimal for the LFB. Moreover, the optimal advertising strategy belongs to a set (a) $S^* \in \{NPM, TL, TF, NC\}$ when $0 < \frac{\phi_L}{\phi_F} < 1$ and (b) $S^* \in \{NPM, TL, NC\}$ when $\frac{\phi_L}{\phi_F} > 1$.

Similar to Proposition 5.3, when the product selling price is endogenously decided, it is not always optimal for the LFB to implement a customized advertising strategy. The optimal implementation of advertising strategy is highly affected by λ and \widehat{F} . When the snobbishness level of Group L is sufficiently high and the fixed cost for planning the customized advertisement is low, the customized advertising strategy is optimal. Besides, regarding the performance of market segmentations for implementing customized advertising strategy, RVCA (i.e., ϕ_L/ϕ_F ⁴⁸) and \widehat{F} are the focal points.

On the other hand, different from what we have uncovered in the basic model, it is interesting to notice that Tactic TF will not always be viewed as a choice of customized advertising strategy when the LFB makes optimal advertising level and selling price decisions simultaneously. According to Proposition 5.8 (i), we know that if RVCA is relatively high, Tactic TF will not be optimal. This phenomenon works for the overall comparison among four discussed cases when the price is a decision. In Proposition 5.3, we find that it is optimal for the LFB to drive away Group F by targeting them with negative publicity when Group L is more snobbish. However, when the LFB endogenously decides the price, the impact of social influences on advertising strategy can be offset by pricing. Due to this reason, even though Group L is highly snobbish, Tactic TF is dominated by other cases when Group F is less sensitive to the advertisement.

⁴⁸ Please refer to Proposition 5.1.

Proposition 5.9. (positive or negative publicity) (i) If $0 < \frac{\phi_L}{\phi_F} < 1$, when λ is relatively high, the negative publicity scheme is optimal for the LFB to implement for (a) Group F under the customized advertising strategy and (b) both groups under non-customized advertising strategy. (ii) If $\frac{\phi_L}{\phi_F} > 1$, when λ is relatively high, the negative publicity scheme is only optimal for the LFB to implement for Group F when the market segmentation is NPM; otherwise, the LFB should implement positive publicity scheme.

Proposition 5.9 further shows that the optimal publicity scheme and corresponding pattern for the publicity implementation are significantly affected by RCVA. If Group F is more sensitive to the advertisement on SMPs compared with Group L consumers, the implementation of positive and negative publicity remains same as the basic model. On the contrary, if Group L is more sensitive to the advertisement, it is less effective for the LFB to implement the negative publicity scheme. Specifically, regarding the optimal implementation of publicity, (i) the negative “uniform publicity” and (ii) negative “polarized publicity” patterns will not be optimal. The reduced effectiveness of negative publicity happens because Group L’s snobbish behavior can be partially offset by the optimal pricing decision which attracts more followers.

5.5.2 Budget Constraints

In the basic model, we examine the case where the LFB launches advertisements without the consideration of budget constraints. However, in real world practices, it is expensive for LFBs to launch advertisement, which makes the budget constraints a crucial factor to take into considerations. For example, as reported, Gucci’s spent about \$567 million on advertising, which is estimated over 10% of its annual revenue in 2020⁴⁹. Therefore, we extend our model to examine the LFB’s SMP advertising strategy with a budget B . We focus on the case with $B > F_b + F_c(x)$ to allow the luxury firm to advertise on SMPs. Based on (5.3) and (5.5), profit functions of the LFB under the customized and non-customized advertising strategies can be described as (5.8) and (5.9), respectively.

⁴⁹ <https://www.g-co.agency/post/gucci-advertising-strategy-case-study>.

$$\begin{aligned} \max_{\xi_L, \xi_F} \Pi^C(\xi_L, \xi_F) &= (p-c)(D_L + D_F) - F_b - F_c(x) - \frac{k\xi_L^2}{2} - \frac{k\xi_F^2}{2}, \\ \text{s.t. } F_b + F_c(x) + \frac{k\xi_L^2}{2} + \frac{k\xi_F^2}{2} &\leq B. \end{aligned} \quad (5.8)$$

$$\begin{aligned} \max_{\xi} \Pi^{NC}(\xi) &= (p-c)(D_L^{NC} + D_F^{NC}) - F_b - \frac{k\xi^2}{2}, \\ \text{s.t. } F_b + \frac{k\xi^2}{2} &\leq B. \end{aligned} \quad (5.9)$$

Note that, considering the budget constraints, the optimization problems can be divided into two situations, namely “budget sufficiency” and “budget insufficiency”. If the budget is sufficient, the optimal decisions should be the same as the basic model where there is no budget constraint. However, if the budget is insufficient, the LFB decides the optimal advertising levels using its entire budget, which differs from the basic model. Therefore, in this extension, we pay attention to exploring the optimal advertising strategy when the firm encounters budget insufficiency and check the robustness of our major findings in the basic model. Similar to the basic model, we examine the NPM and PM market scenarios for the customized advertising strategy. Solving (5.8) and (5.9), we propose Lemma 5.1 that defines the budget insufficiency (P.S.: The thresholds B_{NPM}^{BC} , B_{TL}^{BC} , B_{TL}^{BC} , and B_{TF}^{BC} are provided in Appendix II-C).

Lemma 5.1 *When $B < \min\{B_{NPM}^{BC}, B_{TL}^{BC}, B_{TL}^{BC}, B_{TF}^{BC}\}$, the LFB encounters the budget insufficient situation.*

Lemma 5.1 intuitively shows the minimum thresholds of the budget that the LFB needs to plan advertisement campaigns on SMPs. When $B < \min\{B_{NPM}^{BC}, B_{TL}^{BC}, B_{TL}^{BC}, B_{TF}^{BC}\}$, the LFB should make the optimal advertising level decisions in the face of an insufficient budget for planning advertising campaigns. Therefore, B becomes a crucial factor for the LFB to take into consideration. In the following, comparing customized advertising with the non-customized advertising strategies, we have Proposition 5.10.

Proposition 5.10. (optimal advertising strategy encountering the budget insufficiency) (i) *Under*

the PM scenario, the LFB should select Tactic TL (resp. TF) when $\frac{\phi_L}{\phi_F} > \left| \frac{1-\lambda}{1+\beta} \right|$ (resp. $\frac{\phi_L}{\phi_F} < \left| \frac{1-\lambda}{1+\beta} \right|$). (ii)

Comparing the PM and NPM scenarios, the LFB should present the PM scenario (i.e., TF or TL) when

$\widehat{F} > \max\{\widehat{F}_L^{BC}, \widehat{F}_F^{BC}\}$. (iii) *Comparing the customized and non-customized advertising strategies, it is*

more profitable for the LFB to adopt a customized advertising strategy if and only if $\lambda > 1$ and $\widehat{F} < \max\{\widehat{F}_2^{BC}, \widehat{F}_3^{BC}\}$.

Proposition 5.10 interestingly shows that the implementation of the optimal advertising strategy still depends on the snobbishness level of Group L and the fixed cost of customized advertising paid to the SMP. More importantly, it is still effective to offset the detrimental effect brought by fashion leaders' snobbish behavior by using the customized advertising strategy, while the budget is insufficient. Moreover, checking the derived optimal advertising levels (provided in Appendix II-C), we find that the implementation of positive and negative publicity is in line with the situation where the budget is insufficient. It is because the impacts of budget insufficiency fail to offset the effect of social influences on the optimal advertising levels. Therefore, the LFB should determine the optimal implementation of publicity considering conspicuous behavior as the major factor. In Proposition 5.11, we uncover the interaction of budget and social influences on the optimal advertising levels.

Proposition 5.11. (impacts of budget on optimal advertising levels) (i) *Under the customized advertising strategy (i.e., NPM, TL, and TF), the optimal advertising level for Group L increases in B ; However, the optimal advertising level for Group F increases in B if $\lambda < 1$, and it decreases in B if $\lambda > 1$.* (ii) *Under the non-customized advertising strategy, the optimal advertising level for both groups increases in B if $\lambda < 1 + \frac{(1+\beta)\phi_L}{\phi_F}$, and it decreases in B if $\lambda > 1 + \frac{(1+\beta)\phi_L}{\phi_F}$.*

Common knowledge suggests that a higher budget on advertising results in a higher advertising level. However, Proposition 5.11 reveals an interesting phenomenon: it is not always optimal for the LFB to increase advertising levels when the budget becomes more sufficient. This phenomenon is caused by the interaction of social influences and budget on the LFB's optimal advertising level decisions, which enables the optimality of negative publicity. We know that even though the budget is insufficient, it is still optimal for the LFB to strategically adopt the negative publicity in the same rule (i.e., patterns of publicity) as the basic model. In these situations where negative publicity is adopted, the higher budget enables the LFB to enhance the degree of negative publicity, that is high-level negative publicity. By doing so, the LFB becomes more powerful to drive away followers and ensure profitability from Group L. Therefore, the LFB would decrease the optimal advertising level with a higher budget.

5.6 Summary of This Chapter

Advertising has stepped into the digital era. Planning advertisements on social media platforms (SMPs) is prevalent, especially for luxury fashion brands (LFBs). Advertising on SMPs is characterized by the ability of launching customized advertising conveniently. It is the strategy that LFBs plan advertisements toward groups of consumers with customized content. For example, a French luxury fashion brand, Chloe, launched customized advertisements to promote its “Love Story” fragrance theme. By contrast, some LFBs ignore the customization function for advertising on SMPs, they simply plan the non-specified content to all consumers. For example, Chanel, usually post advertisements to all customers. These observed industrial practices motivate us to explore the customized advertising strategy on SMPs.

We capture unique features of luxury fashion operations, including the consumers’ conspicuous behavior and controversial advertising to examine the optimal advertising strategy. The conspicuous behavior in this work is estimated by social influences. To be specific, fashion leaders (i.e., Group L) treasure status and do not feel good towards the consumption of fashion followers (i.e., Group F); however, Group F group has a desire to follow Group L’s purchasing. Under social influences, whether and when controversial advertising (i.e., negative publicity) is optimal for LFBs to adopt on SMPs deserves our attention. To explore the aforementioned problems, we build analytical models for an LFB that advertises on SMPs. We study two types of advertising strategies, namely the customized advertising strategy and the non-customized advertising strategy. Moreover, under customized advertising, we examine the NPM and PM scenarios. For each scenario, we first derive the optimal advertising level(s) and profits. After that, comparing and analyzing the optimal solutions, we successfully reveal the performance of market segmentation, optimal advertising strategy, and when negative publicity should be implemented. Furthermore, we check the robustness of findings in the basic model by extending our model to (i) endogenously decide the price decision and (ii) consider the budget constraint. In these extensions, several valuable complementary results have been generated as well. We provide key findings which may help managers to improve operations as follows.

Performance of market segmentation under the customized advertising strategy: When the fixed cost for planning customized advertising is relatively higher, it is optimal for the LFB to present the polarized market segmentation, such as TL or TF. This finding implies that it may be optimal for LFBs to advertise towards a selected group, instead of targeting both groups of consumers. Moreover, our finding indicates that, whether the LFB should target Group L or Group F depends on the “*relative value of co-efficient for advertising towards Group L over Group F*”. When this relative value is relatively larger, Tactic TL is superior to TF. It means that the LFB should target the advertisement-sensitive group.

Customized advertising strategy vs. Non-customized advertising strategy: Even though two market segmentations are explored in this work, comparing them with the non-customized advertising strategy, we can see that the customized advertising strategy is not always profitable for the LFB. How to implement the advertising strategy depends on social influences. When the snobbish level of Group L is relatively low, the non-customized advertising strategy is dominant to the customized advertising strategy. However, when the snobbish level of Group L is relatively high the optimality of advertising strategies is determined by the fixed cost for planning customized advertising. Specifically, if it is not costly for the LFB to purchase customized advertising services on SMPs, it will be profitable to adopt the customized advertising strategy in any form of market segmentation (e.g., the NPM scenario, and PM scenario with Tactic TL and Tactic TF). This work highlights the importance for the LFB to pay attention to social influences, especially for the snobbishness, when making the optimal advertising strategy on SMPs.

Implementation of negative publicity: Contrary to the conventional wisdom which points out that advertising campaigns should focus on creating positive publicity so as to enhance demand, we interestingly reveal the importance of negative publicity. It may be profitable for the LFB to plan the negative publicity whether the customized or non-customized advertising strategy is implemented. The negative publicity can be achieved by posting advertisements with controversy, such as racism. Findings show that when adopting the customized advertising strategy, the controversial advertisements should only be posted to Group F to drive them off. By contrast, when the non-customized advertising strategy is adopted, the LFB should launch negative publicity for both groups

of consumers. To the best of our knowledge, ours is the first paper that explores the negative publicity and uncovers the optimal implementation of it in operations management. The generated findings are hence valuable for LFBs to make a wise advertising strategy.

Endogenous price and budget constraint: Extending the basic model to explore cases where (i) the price is endogenously determined and (ii) the budget is insufficient, we prove that findings in the basic model remain valid. Besides, complementary findings related to the pricing decision and effects of budget are obtained. Specifically, when the sales price is endogenously given, it is uncovered that the pricing decision and advertising levels can interactively affect the optimal advertising strategy, which results in the fact that Tactic TF may not be the optimal choice. When the advertising budget is insufficient, we find that the optimal implementation of advertising strategy follows the same rule as the basic model.

Chapter 6 Concluding Remarks

6.1 Conclusions

This thesis focuses on exploring the optimal channel structure and coordination for multi-channel operation, and optimal platform adoption in the e-commerce era. First, considering crucial effects of cross-channel influences, this work develops newsvendor model in a mobile-app and website dual channel scenario, and examines the optimal quantity decision. Second, realizing the prevalence of e-platform, this work examines the optimal channel structure when both the direct online selling (website) and e-platform with commission fee channels are provided for an online retailer. Third, from the perspective of platforms' service function, this work investigates the optimal implementation of social media platform to launch advertisement. The major findings can be summarized as follows.

Coordination of mobile-app-website e-commerce newsvendor supply chain: We analytically derive the optimal ordering decision and uncover that the e-tailer's optimal ordering quantity and the corresponding optimal expected profit are affected by the magnitude of cross-channel influences. Owing to the features of the MA-WS dual channel, we have four models (Models RR, RC, CR and CC) capturing the directional channel reinforcement effect and channel cannibalization effect. However, it is interesting to find that the optimal FET investment level is independent of the cross-channel influence. Then, we show that the dual channel MA-WS e-commerce supply chain system under Nash bargaining can be coordinated by various commonly seen supply chain contracts. For the coordinated (or centralized) e-commerce supply chain system, impacts brought by a larger magnitude of cross-channel influence on the coordination contract parameters settings depend on the specific contract type. Moreover, for the coordinated (or centralized) e-commerce supply chain system, impacts brought by a larger magnitude of cross-channel influence on the centralized e-commerce supply chain's optimal ordering quantity and the corresponding optimal expected profit follow the same pattern as in the e-tailer's case under the decentralized uncoordinated supply chain setting. From these results, we reveal that for the coordinated e-commerce supply chain system, whether it is optimal to delink channels or strengthen cross-channel influences follows the results in Table 3.12. We highlight a few insights: First, the optimal "delink" or "strengthen" decisions relate to the specific directional

cross-channel influence. For instance, under Model RC, it is always wise to delink the M2W (mobile app to website) channel while it is wise to strengthen the W2M (website to mobile app) channel if the M2W channel influence is sufficiently small. Second, whether to choose delink or strength depends on models. The corresponding pattern follows whether increasing or decreasing magnitude of a cross-channel influence will lead to a higher expected profit for the e-commerce supply chain system. Since the e-commerce supply chain is coordinated under Nash bargaining model, a higher e-commerce supply chain expected profit directly implies a higher profit for each channel member. Third, for the models involving “R”, i.e., the channel reinforcement effect (cf.: Model RR, Model RC and Model CR), the optimal decision on “delink” and “strengthen” a particular cross-channel influence may depend on the size of the cross-channel influence. Finally, we consider the probable use of blockchain to improve the effectiveness of FET investment. We uncover that whether the e-tailer should consider implementing blockchain highly depends on the per period fixed blockchain operations cost (for both the decentralized uncoordinated, and centralized/coordinated e-commerce supply chains). It is interesting to observe that the use of blockchain or not does not affect the optimal decisions on “delink” channels or “strengthen” cross-channel influences. This is an important result as it implies that the e-tailer can do two enhancements, implementing blockchain (to improve demand forecasting) and redesigning the website (with “delink and strengthen”), without worrying about one another as they are independent. Furthermore, if it is optimal to use blockchain, when we check the impacts brought by changes of the cross-channel influences, we will find that the same pattern as in the cases without blockchain appears.

Optimal e-tailing channel structure and service contracting in e-platform and direct selling dual channel: First, we theoretically illustrate how the RSF service fee contract can maximize the ET-PF system. Second, we examine three models, namely the (pure) direct-online (DO) sales channel, the pure e-platform (PP) sales channel, and the dual direct-online and e-platform (DP) sales channel. For each model, the optimal pricing decision is derived. Third, an algorithm that helps achieve robust systems optimization (i.e., achieving systems optimization and allowing flexible profit allocation between the e-tailer and e-platform) is developed. Finally, we test robustness of the results by examining three extensions. For the extension in which the product is produced by a separate

manufacturer and then supplied to the e-tailer, provided that a suitable supply contract is implemented to achieve “internal coordination” of this product supply chain, we show that all the findings in the basic models remain valid. For the extended analyses on consumer surplus and social welfare, we find that the RSF service contract can help achieve systems optimization in social welfare. For the extension when the e-tailer considers both product quality and retail product pricing decisions, we uncover that the RSF service contract fails to achieve robust systems optimization. As a remedial solution, we propose the use of a cost-sharing RSF service contract to help and show that it works well. Managerial implications are discussed.

The optimal implementation of social media platform based advertising strategy for luxury fashion brands: Comparing optimal decisions and profits among various considered cases, we analytically identify that social influences (e.g., the snobbishness of leaders), fixed costs for planning customized advertising, and co-efficient of advertising levels to demand functions are important factors in determining the optimal advertising strategy, publicity scheme (i.e., positive publicity versus negative publicity), and the value of social influences. First, exploring the implementation of customized and non-customized advertising strategies, we find that the non-customized advertising strategy is dominant when the snobbishness level of fashion leaders is sufficiently low. However, when the snobbishness level is sufficiently high, it is optimal for the LFB to implement the customized advertising strategy if the fixed cost for planning customized advertising is sufficiently low. This finding highlights the significant effect of consumers’ conspicuous behavior (i.e., social influences) when advertising on SMPs. Second, we interestingly reveal that controversial advertisements (i.e., negative publicity) could be optimal for the LFB in some cases. For example, when the snobbishness level of Group L is relatively high, it is wise to drive away fashion followers by creating negative publicity. Moreover, we find that the negative publicity is more profitable under the customized advertising strategy compared with the non-customized advertising strategy. Third, exploring the scenario without social influences, we reveal that the non-customized advertising strategy is always optimal, which verifies the value of social influences to the customized advertising strategy. Last but not least, we extend our model to cases where (i) retail price is endogenously determined and (ii) the

budget of advertising campaigns is constrained. We find that the major findings remain valid in these two extensions. Besides, the effects of pricing and the budget constraint have been uncovered as well.

To conclude, from the perspective of multi-channel operations, this doctoral thesis research analytically explores the optimal channel structure and coordination strategy when different types of dual-channel operations are adopted (i.e., mobile-apps-website and e-platform-website) with the consideration of cross-channel influences. On the other hand, in the view of platform management, this thesis examines the optimal implementation of two types of platforms, namely the product selling platforms and social media platforms, with the objective to improve the retailer's profits in the digital era.

6.2 Future Studies

In this sub-chapter, several future studies are presented from the perspective of model settings and research topics.

First of all, the model settings of this thesis can be further extended. (i) We consider the single-period and single firm setting in three analytical chapters, and further research can be extended to consider the situation with multiple periods or multi-firms (Li 2018). For example, competitive models (Guo et al. 2020) among multiple e-tailers or e-platforms can be a future avenue for further studies. (ii) Operations of e-commerce always face risk and uncertainty, further studies can be conducted to include stochastic factors, and then risk analysis can be carried out (Zhang et al. 2020b). (iii) In Chapter 5, we capture consumers' conspicuous behavior (i.e., social influences) utilizing the inter-related demand function (see, e.g., Chiu et al. 2018). We propose future studies to consider a social status model (Li 2019) which explores the advertising strategy as well as the consumers' choice of being fashion leaders and fashion followers. (iv) In Chapter 3 and Chapter 5, the optimal channel strategy is explored for the operations of fashionable products. It is promising to explore the properties of durable products in multi-channel and platform operations. (v) In Chapter 3 and Chapter 4, we explore the impacts of cross channel influences instead of the decision on the optimal cross channel influences. It is important to investigate the optimal cross-channel influences in the future.

Secondly, this doctoral thesis can be extended with different research questions regarding the multi-channel operations and platform management in the e-commerce and industry 4.0 era. (i) In Chapter 3 and Chapter 4, this work focuses on a dual channel circumstance considering the implementation of mobile app or e-platform when the website selling channel is deployed. We intentionally do not include the physical stores so that we can focus on exploring the effect of cross-channel influences on the mobile and website channel operations. In future research, we do plan to examine the situation when mobile app sales channel, website channel and physical store all exist. In this situation, the impacts of cross channel effects would be more complex, which would be valuable to explore. (ii) Regarding the implementation of platforms in e-commerce, Chapter 4 and Chapter 5 examine the optimal adoption of product selling platforms and social media platforms. They are still several types of platforms that are deployed in e-commerce in practice, such as on-demand platforms, which are valuable to explore in the future. (iii) In the industry 4.0 era, it is crucial to explore the use of technology in improving multi-channel operations and platform management. For example, with the help of big data, e-tailers can offer personalized services and products to individual consumers; implementing blockchain (Michelman 2017) in platform management is prevalent, especially its feature of achieving information transparency (Huang and Yang 2016), More studies can proceed along this line in the future to facilitate e-platform based e-commerce.

References

- Amaldoss, W., C. He. 2010. Product variety, informative advertising, and price competition. *Journal of Marketing Research*, 47(1), 146-156.
- Amaldoss, W., S. Jain. 2010. Reference groups and product line decisions: an experimental investigation of limited editions and product proliferation. *Management Science*, 56(4), 621– 644.
- Amaldoss, W., S. Jain. 2015. Branding conspicuous goods: an analysis of the effects of social influence and competition. *Management Science*, 61(9), 2064-2079.
- Amrouche, N., Z. Pei, R. Yan. 2020. Mobile channel and channel coordination under different supply chain contexts. *Industrial Marketing Management*, 84, 165-182.
- Arifoğlu, K., S. Deo, S. M. Iravani. 2020. Markdowns in seasonal conspicuous goods. *Marketing Science*, 39(5), 1016-1029.
- Asian, S., X. Nie. 2014. Coordination in supply chains with uncertain demand and disruption risks: Existence, analysis, and insights. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 44(9), 1139-1154.
- Aviv, Y., M. M. Wei., F. Zhang. 2019. Responsive pricing of fashion products: The effects of demand learning and strategic consumer behavior. *Management Science*, 65(7), 2982-3000.
- Bai, J., K. C. So, C. S. Tang, X. Chen, H. Wang. 2019. Coordinating supply and demand on an on-demand service platform with impatient customers. *Manufacturing & Service Operations Management*, 21(3), 556-570.
- Balapour, A., H.R. Nikkhah, R. Sabherwal. 2020. Mobile application security: Role of perceived privacy as the predictor of security perceptions. *International Journal of Information Management*, 52, 102063.
- Bell, D., S. Gallino, A. Moreno. 2015. Showrooms and information provision in omni-channel retail. *Production and Operations Management*, 24(3): 360–362.
- Bell, D., S. Gallino, A. Moreno. 2017. Offline showrooms in omni-channel retail: Demand and operational benefits. *Management Science*, 64(4): 1629–1651.

- Bellos, I., M. Ferguson, L. B. Toktay. 2017. The car sharing economy: Interaction of business model choice and product line design. *Manufacturing & Service Operations Management*, 19(2), 185-201.
- Benjaafar, S., G. Kong, X. Li, C. Courcoubetis. 2019. Peer-to-peer product sharing: Implications for ownership, usage, and social welfare in the sharing economy. *Management Science*, 65(2), 477-493.
- Berger, J., A. T. Sorensen, S. J. Rasmussen. 2010. Positive effects of negative publicity: When negative reviews increase sales. *Marketing Science*, 29(5), 815-827.
- Bhargava, H. K., B. C. Kim, D. Sun. 2013. Commercialization of platform technologies: Launch timing and versioning strategy. *Production and Operations Management*, 22(6), 1374-1388.
- Cachon, G. P., M. A. Lariviere. 2005. Supply chain coordination with revenue-sharing contracts: strengths and limitations. *Management science*, 51(1), 30-44.
- Cachon, G. P., K. M. Daniels, R. Lobel. 2017. The role of surge pricing on a service platform with self-scheduling capacity. *Manufacturing & Service Operations Management*, 19(3), 368-384.
- Cai, G. G., Z. G. Zhang, M. Zhang. 2009. Game theoretical perspectives on dual-channel supply chain competition with price discounts and pricing schemes. *International Journal of Production Economics*, 117(1), 80-96.
- Cai, G. G. 2010. Channel selection and coordination in dual-channel supply chains. *Journal of Retailing*, 86(1), 22-36.
- Cai, Y. J., T. M. Choi, J. Zhang. 2021. Platform supported supply chain operations in the blockchain era: Supply contracting and moral hazards. *Decision Sciences*, 52(4), 866-892.
- Chatterjee, P., B. Zhou. 2021. Sponsored content advertising in a two-sided market. *Management Science*, 67(12), 7560-7574.
- Chen, Y. J., T. Dai, C. G. Korpeoglu, E. Körpeoğlu, O. Sahin, C. S. Tang, S. Xiao. 2020. OM forum—Innovative online platforms: Research opportunities. *Manufacturing & Service Operations Management*, 22(3), 430-445.
- Chen, Y., Q. Liu. 2021. Signaling through advertising when ad can be blocked. *Marketing Science*, 41(1), 166-187.

- Chen, Y. J., J. G. Shanthikumar, Z. J. M. Shen. 2015. Incentive for peer-to-peer knowledge sharing among farmers in developing economies. *Production and Operations Management*, 24(9), 1430-1440.
- Chiang, W. Y. K., D. Chhajed, J. D. Hess. 2003. Direct marketing, indirect profits: A strategic analysis of dual-channel supply-chain design. *Management science*, 49(1), 1-20.
- Chiu, C. H., T. M. Choi, X. Dai, B. Shen, J. H. Zheng. 2018. Optimal advertising budget allocation in luxury fashion markets with social influences: a mean-variance analysis. *Production and Operations Management*, 27(8), 1611-1629.
- Choi, T. M. 2020a. Financing product development projects in the blockchain era: Initial coin offerings versus traditional bank loans. *IEEE Transactions on Engineering Management*, published online.
- Choi, T. M. 2020b. Mobile-app-online-website dual channel strategies: Privacy concerns, e-payment convenience, channel relationship, and coordination. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 51(11), 7008-7016.
- Choi, T. M. 2021. Facing market disruptions: values of elastic logistics in service supply chains. *International Journal of Production Research*, 59(1), 286-300.
- Choi, T. M., S. Guo, N. Liu, X. Shi. 2020. Optimal pricing in on-demand-service-platform-operations with hired agents and risk-sensitive customers in the blockchain era. *European Journal of Operational Research*, 284(3), 1031-1042.
- Choi, T. M., Y. He. 2019. Peer-to-peer collaborative consumption for fashion products in the sharing economy: Platform operations. *Transportation Research Part E: Logistics and Transportation Review*, 126, 49-65.
- Choi, T.M., S. Luo. 2019. Data quality challenges for sustainable fashion supply chain operations in emerging markets: Roles of blockchain, government sponsors and environment taxes. *Transportation Research Part E: Logistics and Transportation Review*, 131, 139-152.
- Choi, T. M., S. W. Wallace, Y. Wang. 2018. Big data analytics in operations management. *Production and Operations Management*, 27(10), 1868-1883.

- Choi, T.M., X. Wen, X. Sun, S.H. Chung. 2019. The mean-variance approach for global supply chain risk analysis with air logistics in the blockchain technology era. *Transportation Research Part E: Logistics and Transportation Review*, 127, 178-191.
- Choi, T.M., J. Zhang, T.C.E. Cheng. 2018. Quick response in supply chains with stochastically risk sensitive retailers. *Decision Sciences*, 49(5), 932-957.
- Chutani, A., S. P. Sethi. 2018. Dynamic cooperative advertising under manufacturer and retailer level competition. *European Journal of Operational Research*, 268(2), 635-652.
- Degirmenci, K. 2020. Mobile users' information privacy concerns and the role of app permission requests. *International Journal of Information Management*, 50, 261-272.
- Dong, C., C. T. Ng, T. C. E. Cheng. 2017. Electricity time-of-use tariff with stochastic demand. *Production and Operations Management*, 26(1), 64-79.
- Donohue, K. L. 2000. Efficient supply contracts for fashion goods with forecast updating and two production modes. *Management Science*, 46(11), 1397-1411.
- Du, S., L. Wang, L. Hu, Y. Zhu. 2019. Platform-led green advertising: Promote the best or promote by performance. *Transportation Research Part E: Logistics and Transportation Review*, 128, 115-131.
- Feng, J., J. Xie. 2012. Research Note—Performance-based advertising: Advertising as signals of product quality. *Information Systems Research*, 23(3-part-2), 1030-1041.
- Gal-Or, E. 2004. Evaluating the profitability of product bundling in the context of negotiations. *The Journal of Business*, 77(4), 639-674.
- Gal-Or, E., M. Gal-Or. 2005. Customized advertising via a common media distributor. *Marketing Science*, 24(2), 241-253.
- Gan, X., S. P. Sethi, H. Yan. 2005. Channel coordination with a risk-neutral supplier and a downside-risk-averse retailer. *Production and Operations Management*, 14(1), 80-89.
- Gao, D., N. Wang, B. Jiang, J. Gao, Z. Yang. 2020. Value of information sharing in online retail supply chain considering product loss. *IEEE Transactions on Engineering Management*, published online.

- Gao, F., X. Su. 2016. Online and offline information for omnichannel retailing. *Manufacturing & Service Operations Management*, 19(1), 84-98.
- Gao, F., X. Su. 2017. Omnichannel retail operations with buy-online-and-pickup-in-store. *Management Science*, 63(8), 2478–2492.
- Gao, F., X. Su. 2018. Omnichannel service operations with online and offline self-order technologies. *Management Science*, 64(8), 3595-3608.
- Gao, S. Y., W. S. Lim, C. S. Tang. 2017. Entry of copycats of luxury brands. *Marketing Science*, 36(2), 272-289.
- Geng, Q., S. Mallik. 2007. Inventory competition and allocation in a multi-channel distribution system. *European Journal of Operational Research*, 182(2), 704-729.
- Gould, J. P. 1976. Diffusion processes and optimal advertising policy. *Mathematical Models in Marketing* (pp. 169-174), Springer, Berlin, Heidelberg.
- Guo, S., T. M. Choi, B. Shen. 2020. Green product development under competition: A study of the fashion apparel industry. *European Journal of Operational Research*, 280(2), 523-538.
- Gupta, R., K. Jain. 2014. Adoption of mobile telephony in rural India: An empirical study. *Decision Sciences*, 45(2), 281-307.
- Ha, A. Y., S. Tong, Y. Wang. 2021. Channel structures of online retail platforms. *Manufacturing & Service Operations Management*, published online.
- Ha, A. Y., H. Luo, W. Shang. 2022. Supplier encroachment, information sharing, and channel structure in online retail platforms. *Production and Operations Management*, 31(3), 1235-1251.
- Han, Y. J., J. C. Nunes, X. Dreze. 2010. Signaling status with luxury goods: the role of brand prominence. *Journal of Marketing*, 74(4), 15-30.
- Hartl, R. F., A. J. Novak, A. G. Rao, S. P. Sethi. 2003. Optimal pricing of a product diffusing in rich and poor populations. *Journal of Optimization Theory and Applications*, 117(2), 349-375.
- Heydari, J., T. M. Choi, S. Radkhah. 2017. Pareto improving supply chain coordination under a money-back guarantee service program. *Service Science*, 9(2), 91-105.

- Hitt, L. M., E. Brynjolfsson. 1996. Productivity, business profitability, and consumer surplus: three different measures of information technology value. *Management Information Systems Quarterly*, 121-142.
- Hu, Y., J. Shin, Z. Tang. 2016. Incentive problems in performance-based online advertising pricing: Cost per click vs. cost per action. *Management Science*, 62(7), 2022-2038.
- Hua, G., S. Wang, T. C. E. Cheng. 2012. Optimal pricing and order quantity for the newsvendor problem with free shipping. *International Journal of Production Economics*, 135(1), 162-169.
- Huang, J., M. Leng, L. Liang. 2012. Recent developments in dynamic advertising research. *European Journal of Operational Research*, 220(3), 591-609.
- Huang, J., M. Leng, M. Parlar. 2013. Demand functions in decision modeling: A comprehensive survey and research directions. *Decision Sciences*, 44(3), 557-609.
- Huang, L., X. Lu, S. Ba. 2016. An empirical study of the cross-channel effects between web and mobile shopping channels. *Information & Management*, 53(2), 265-278.
- Huang, S., J. Yang. 2016. Information acquisition and transparency in a supply chain with asymmetric production cost information. *International Journal of Production Economics*, 182, 449-464.
- Huang, Z., S. X. Li. 2001. Co-op advertising models in manufacturer–retailer supply chains: A game theory approach. *European Journal of Operational Research*, 135(3), 527-544.
- Ishfaq, R., N. Bajwa. 2019. Profitability of online order fulfillment in multi-channel retailing. *European Journal of Operational Research*, 272(3), 1028-1040.
- Iyer, A.V., M.E. Bergen. 1997. Quick response in manufacturer-retailer channels. *Management Science* 43(4), 559-570.
- Iyer, G., D. Soberman, J. M. Villas-Boas. 2005. The targeting of advertising. *Marketing Science*, 24(3), 461-476.
- Jing, B. 2018. Showrooming and webrooming: Information externalities between online and offline sellers. *Marketing Science*, 37(3), 469-483.
- Jiang, L., S. Dimitrov, B. Mantin. 2017. P2P marketplaces and retailing in the presence of consumers' valuation uncertainty. *Production and Operations Management*, 26(3), 509-524.

- Jørgensen, S., S. Taboubi, G. Zaccour. 2003. Retail promotions with negative brand image effects: Is cooperation possible? *European Journal of Operational Research*, 150(2), 395-405.
- Joshi, Y. V., D. J. Reibstein, Z. J. Zhang. 2009. Optimal entry timing in markets with social influence. *Management Science*, 55(6), 926-939.
- Katewa, S., T. Jain. 2020. Mobile application's quality and pricing decisions under competition. *Decision Sciences*, published online.
- Kennedy, A. P., S. P. Sethi, C. C. Siu, S. C. P. Yam. 2021. Co-op advertising in a dynamic three-echelon supply chain. *Production and Operations Management*, published online.
- Kireyev, P., V. Kumar, E. Ofek. 2017. Match your own price? Self-matching as a retailer's multichannel pricing strategy. *Marketing Science*, 36(6), 908-930.
- Ko, E., J. P. Costello, C. R. Taylor. 2019. What is a luxury brand? A new definition and review of the literature. *Journal of Business Research*, 99, 405-413.
- Kuksov, D., K. Wang. 2013. A model of the "it" products in fashion. *Marketing Science*, 32(1), 51-69.
- Kuksov, D., R. Shachar, K. Wang. 2013. Advertising and consumers' communications. *Marketing Science*, 32(2), 294-309.
- Kung, L. C., G. Y. Zhong. 2017. The optimal pricing strategy for two-sided platform delivery in the sharing economy. *Transportation Research Part E: Logistics and Transportation Review*, 101, 1-12.
- Lakemond, N., G. Holmberg, A. Pettersson. 2021. Digital transformation in complex systems. *IEEE Transactions on Engineering Management*, published online.
- Lee, C. H., T. M. Choi, T. C. E. Cheng. 2021. Operations strategies with snobbish and strategic consumers. *Naval Research Logistics*, 68(3), 327-343.
- Li, G., Z.P. Fan, X.Y. Wu. 2021. The choice strategy of authentication technology for luxury e-commerce platforms in the blockchain era. *IEEE Transactions on Engineering Management*, published online.
- Li, K.J. 2019. Status goods and vertical line extensions. *Production and Operations Management*, 28(1), 103-120.

- Liu, D., S. Kumar, V. S. Mookerjee. 2012. Advertising strategies in electronic retailing: A differential games approach. *Information Systems Research*, 23, 903-917.
- Liu, W., D. Wang, X. Shen, X. Yan, W. Wei. 2018. The impacts of distributional and peer-induced fairness concerns on the decision-making of order allocation in logistics service supply chain. *Transportation Research Part E: Logistics and Transportation Review*, 116, 102-122.
- Liu, Y, P. Yildirim, Z. J. Zhang. 2021. Implications of revenue models and technology for content moderation strategies. Available at SSRN: <http://dx.doi.org/10.2139/ssrn.3969938>.
- Long, F., K. Jerath, M. Sarvary. 2022. Designing an online retail marketplace: Leveraging information from sponsored advertising. *Marketing Science*, 41(1), 115-138.
- Mahajan, V., E. Muller. 1986. Advertising pulsing policies for generating awareness for new products. *Marketing Science*, 5(2), 89-106.
- Mantena, R., R. Sankaranarayanan, S. Viswanathan. 2010. Platform-based information goods: The economics of exclusivity. *Decision Support Systems*, 50(1), 79-92.
- Mauss, M. 2002. The gift: The form and reason for exchange in archaic societies. *Routledge*.
- Michelman P. 2017. Seeing beyond the blockchain hype. *MIT Sloan Management Review*, vol. 58, pp. 17-19.
- Nagurney, A., M. Yu. 2012. Sustainable fashion supply chain management under oligopolistic competition and brand differentiation. *International Journal of Production Economics*, 135(2), 532-540.
- Niu, B., L. Wang, J. Dong. 2022. Enabling emergency production shifting: The value of blockchain in supply chain resilience confronting COVID-19. Available at SSRN 4061325.
- Ozga, S. A. 1960. Imperfect markets through lack of knowledge. *Quarterly Journal of Economics*, 29-52.
- Park, Y., Y. Bang, J.H. Ahn. 2020. How does the mobile channel reshape the sales distribution in e-commerce? *Information Systems Research*, 31(4), 1164-1182.
- Porteus, E. L. 2002. *Foundations of stochastic inventory theory*. Stanford University Press.
- Rafieian, O., H. Yoganarasimhan. 2021. Targeting and privacy in mobile advertising. *Marketing Science*, 40(2), 193-218.

- Ryan, J. K., D. Sun, X. Zhao. 2012. Competition and coordination in online marketplaces. *Production and Operations Management*, 21(6), 997-1014.
- Schoenbachler, D. D., G. L. Gordon. 2002. Multi-channel shopping: Understanding what drives channel choice. *Journal of Consumer Marketing*, 19(1), 42-53.
- Sethi, S. P. 1977. Optimal advertising for the Nerlove-Arrow model under a budget constraint. *Operational Research Quarterly*, 28(3), 683-693.
- Sethi, S. P. 1983. Deterministic and stochastic optimization of a dynamic advertising model. *Optimal Control Applications and Methods*, 4(2), 179-184.
- Sethi, S. P. 2018. *Optimal Control Theory*. Cham: Springer International Publishing AG.
- Sharma, V. 2019. Blockchain – its role in demand and supply planning. *Journal of Business Forecasting*, 38(4), 9-11.
- Shen, B., X. Xu, Q. Yuan. 2020. Selling secondhand products through an online platform with blockchain. *Transportation Research Part E: Logistics and Transportation Review*, 142, 102066.
- Shen, Y., S. P. Willems, Y. Dai. 2019. Channel selection and contracting in the presence of a retail platform. *Production and Operations Management*, 28(5), 1173-1185.
- Shi, X., H.L. Chan, C. Dong. 2020. Value of bargaining contract in a supply chain system with sustainability investment: An incentive analysis. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 50(4), 1622 - 1634.
- Shin, J., K. Sudhir. 2013. Should you punish or reward current customers? *MIT Sloan Management Review*, 55(1), 59.
- Sun, L., R. H. Teunter, M. Z. Babai, G. Hua. 2019. Optimal pricing for ride-sourcing platforms. *European Journal of Operational Research*, 278(3), 783-795.
- Taylor, T. A. 2002. Supply chain coordination under channel rebates with sales effort effects. *Management science*, 48(8), 992-1007.
- Tian, L., Vakharia, A. J., Tan, Y., & Xu, Y. (2018). Marketplace, reseller, or hybrid: Strategic analysis of an emerging e - commerce model. *Production and Operations Management*, 27(8), 1595-1610.

- Tiwana, A., B. Konsynski, A. A. Bush. 2010. Research commentary—Platform evolution: Coevolution of platform architecture, governance, and environmental dynamics. *Information systems research*, 21(4), 675-687.
- Tsay, A.A., N. Agrawal. 2004. Channel conflict and coordination in the e-commerce age. *Production and Operations Management*, 13(1), 93-110.
- Tucker, C. E. 2014. Social networks, personalized advertising, and privacy controls. *Journal of Marketing Research*, 51(5), 546-562.
- Veblen, T. 1899. The theory of the leisure class. Reprint from Penguin, *New York*, 1994.
- Verhoef, P. C., P. K. Kannan, J. J. Inman. 2015. From multi-channel retailing to omni-channel retailing: Introduction to the special issue on multi-channel retailing. *Journal of Retailing*, 91(2), 174-181.
- Vigneron, F., L. W. Johnson. 1999. A review and a conceptual framework of prestige-seeking consumer behavior. *Academy of Marketing Science Review*, 1(1), 1-15.
- Vigneron, F., L. W. Johnson. 2004. Measuring perceptions of brand luxury. *Journal of Brand Management*, 11(6), 484-506.
- Waller, D. S. 2006. A proposed response model for controversial advertising. *Journal of Promotion Management*, 11(2-3), 3-15.
- Wang, R., Q. Guo, T.M. Choi, L. Liang. 2018. Advertising strategies for mobile platforms with "apps". *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 48 (5), 767-778.
- Wang, X., F. He, H. Yang, H. O. Gao. 2016. Pricing strategies for a taxi-hailing platform. *Transportation Research Part E: Logistics and Transportation Review*, 93, 212-231.
- Wang, X., C. T. Ng, C. Dong. 2020. Implications of peer-to-peer product sharing when the selling firm joins the sharing market. *International Journal of Production Economics*, 219, 138-151.
- Wang, Y., L. Jiang, Z. J. Shen. 2004. Channel performance under consignment contract with revenue sharing. *Management Science*, 50(1), 34-47.
- Wang, Y. Y., C. Guo, A. Susarla, V. Sambamurthy. 2021. Online to offline: the impact of social media on offline sales in the automobile industry. *Information Systems Research*, 32(2), 582-604..
- Wang, Y., S. W. Wallace, B. Shen, T. M. Choi. 2015. Service supply chain management: A review of operational models. *European Journal of Operational Research*, 247(3), 685-698.

- Wang, Z. 2018. Delivering meals for multiple suppliers: Exclusive or sharing logistics service. *Transportation Research Part E: Logistics and Transportation Review*, 118, 496-512.
- Wen, W., F. Zhu. 2019. Threat of platform-owner entry and complementor responses: Evidence from the mobile app market. *Strategic Management Journal*, 40, 1336-1367.
- Wen, X., T.M. Choi, S.H. Chung. 2019. Fashion retail supply chain management: A review of operational models. *International Journal of Production Economics*, 207, 34-55.
- Wen, X., T. Siqin. 2020. How do product quality uncertainties affect the sharing economy platforms with risk considerations? A mean-variance analysis. *International Journal of Production Economics*, 224, 107544.
- Wu, D., G.D. Moody, J. Zhang, P.B. Lowry. 2020. Effects of the design of mobile security notifications and mobile app usability on users' security perceptions and continued use intention. *Information and Management*, 57(5), 103235.
- Xu, J., X. Zhou, J. Zhang, D. Z. Long. 2021. The optimal channel structure with retail costs in a dual-channel supply chain. *International Journal of Production Research*, 59(1), 47-75.
- Xu, X., M. Zhang, P. He. 2020. Coordination of a supply chain with online platform considering delivery time decision. *Transportation Research Part E: Logistics and Transportation Review*, 141, 101990.
- Yan, N., Y. Liu, X. Xu, X. He. 2020. Strategic dual-channel pricing games with e-retailer finance. *European Journal of Operational Research*, 283(1), 138-151.
- Yoganarasimhan, H. 2012. Cloak or flaunt? The fashion dilemma. *Marketing Science*, 31(1), 74-95.
- Yoo, S. H., T. Cheong. 2018. Quality improvement incentive strategies in a supply chain. *Transportation Research Part E: Logistics and Transportation Review*, 114, 331-342.
- Zeng, F., H. K. Chan, K. Pawar. 2020. The adoption of open platform for container bookings in the maritime supply chain. *Transportation Research Part E: Logistics and Transportation Review*, 141, 102019.
- Zennyo, Y. 2020. Strategic contracting and hybrid use of agency and wholesale contracts in e-commerce platforms. *European Journal of Operational Research*, 281(1), 231-239.

- Zhang, X. 2009. Retailers' multichannel and price advertising strategies. *Marketing Science*, 28(6), 1080-1094.
- Zhang, J., S. P. Sethi, T. M. Choi, T. C. E. Cheng. 2020b. Supply chains involving a mean-variance-skewness-kurtosis newsvendor: analysis and coordination. *Production and Operations Management*, 29(6), 1397-1430.
- Zhang, L, J. Wang. 2017. Coordination of the traditional and the online channels for a short-life-cycle product. *European Journal of Operational Research*, 258(2), 639-651.
- Zhang, T., G. Li, T.C.E. Cheng, S. Shum. 2020a. Consumer inter-product showrooming and information service provision in an omni-channel supply chain. *Decision Sciences*, 51(5), 1232-1264.

Appendix I Supplementary Information

1. The “3As” framework for platform operations in the 4.0 era⁵⁰

We propose a framework that aims to indicate how platforms should “adopt” advanced technologies to “address” the operational issues to “achieve” the operational outcomes (as depicted in Figure 5). Therefore, we call it the “3As” platform operations framework (the “3As” framework, for short). To address the research questions, we consider that this “3As” framework contains four components, including advanced technologies (component 1), platform operational issues (component 2), outcomes (component 3), platforms (component 4). Based on the observations from the literature review and case studies, the “3As” framework also indicates three developments—collaborations, transformations, and regulations—to reveal the operational directions within each component and highlight the importance of regulations. Specifically, the *collaborations* development entails *technology* and *operational collaborations*, which are represented by the operations integrating two or more technologies and operational issues, respectively. Furthermore, the *transformations* development implies the change of platform types within the platform component. Moreover, the “3As” framework suggests that platform operations in the Industry 4.0 era impose a high demand for monitoring *regulations*. We introduce the three aforementioned developments (i.e., transformations, collaborations, and regulations) of the “3As” framework in the following.

⁵⁰ A part of this Appendix has been published in “Siqin, T., Choi, T.M., Chung, S.H., Wen, X. (2022). Platform operations in the industry 4.0 era: Recent advances and the “3As framework”. *IEEE Transactions on Engineering Management*, 10.1109/TEM.2021.3138745.”

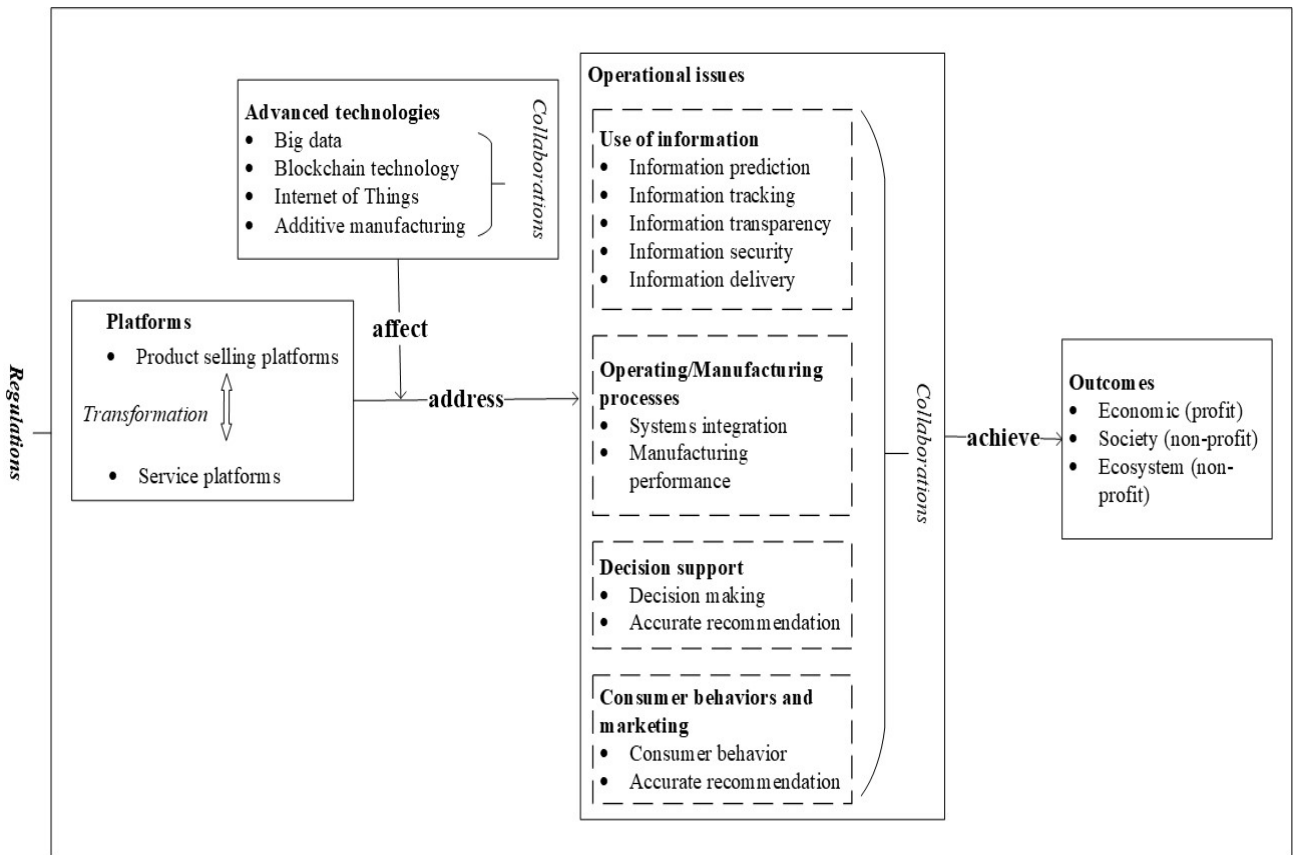


Figure A-1. The “3As” framework.

Collaborations: On one hand, *technology collaborations* are common. From the discussion in literature review part (refer to the published paper), we see that sometimes, the advanced technologies are applied by platforms alone (e.g., only big data or blockchain). Whereas, it is crucial for platforms to implement multiple technologies to support specific operational issues as pointed by Olsen and Tomlin (2020). We call it *technology collaborations*, which means two or more technologies are integrated to support platform operations. The collaboration of advanced technologies enables further improvements for the performance of platforms. For example, “Big data and IoT” collaboration has been well reported in the literature and practice for different platforms. In this combination, big data analytics is transformed to become physical devices-oriented, which significantly differs from the sole implementation of big data technology. Specifically, in the “Big data and IoT” combination, IoT collects data from physical devices, while big data analyzes the collected data and provides the analysis results back to the IoT-based devices. For example, SAP launched a failure prediction project to monitor the working status of equipment. This project is conducted by using the “Big data and IoT”

collaboration, where the operations data are collected from the IoT sensors. Similarly, “IoT and BT” collaboration has been applied in improving the management of information, such as enhancing information completeness and transparency in cloud-based platforms (Rahman et al., 2020).

However, the operational categories are correlated, and we call it *operational collaborations*. It means that, with the help of technologies, platform operations can be improved in multiple operational categories. For instance, improvements in the UOI can lead to better performance in DCS, such as more accurate decision-making and recommendations. The UOI functions as a prerequisite to promote DCS, whereby information prediction and information tracking are the two major functions (Morente-Molinera et al., 2016; Wu et al., 2020). The correlated improvements of operational categories can be viewed as operational collaborations.

Transformations: Driven by the wide implementations of technologies, it is crucial for platforms to conduct transformation and upgrading in the Industry 4.0 era. It not only includes the transformation of platform functions (between PS and service platforms), but also the sides of platforms (among OS, TS, and NS). From a function transformation perspective, it is observed that PS platforms are gradually putting more efforts into offering innovative services by implementing advanced technologies. For instance, Brynjolfsson et al. (2019) explore the implementation of the AI translation service in eBay, a traditional PS platform, to support international trade. As revealed by Brynjolfsson et al. (2019), eBay starts to transform from a onefold PS platform to a multifold platform that sells products and provides services. Furthermore, according to the case study of Facebook, we see that this enterprise provides a marketplace to sell products to local consumers with the help of big data analytics⁵¹. It means that Facebook, a typical service platform, intends to be a multifold platform by incorporating the PS function into the business structure. From the perspective of platform sides, many platforms are trying to expand their interfaces to connect more groups of users. For example, Rahman et al. (2020) study the operations of a cloud platform, which provides data sharing services for n-sided groups of users instead of two sides by using IoT.

Regulations: The operations of platforms have been questioned by users, governments, the market, and other parties. With the implementation of advanced technologies, doubts are growing. This is

⁵¹ <https://www.facebook.com/business/marketplace> accessed on 8 April 2021.

because platforms become more powerful in certain operations, including information access and decision-making, once advanced technologies are applied. Regulations on platform operations are hence essential. In 2020, some countries and areas, such as the United States, European Union, United Kingdom, Japan, and China, released stricter regulations for digital platforms (e.g., Amazon, Facebook, Google) (Sokol & Van Alstyne, 2021). These regulations will certainly affect the operational mode of platforms while preventing potential risks from various aspects, including (i) preventing the dominant force of platforms control in market competition (Cutolo et al., 2021), (ii) reducing the leakage of user privacy, and (iii) reducing illegal operations (Libert et al., 2018).

Observe that the “3As” framework is related to but different from the frameworks proposed in previous research. For example, Gawer (2014) dissects the features of technological platforms from the perspective of the organizational continuum. In Gawer (2014), three types of platforms (i.e., internal, supply chain, and industry platforms) are identified regarding different organizational forms, interfaces, accessible scope, and governance. Based on the discussion of platform types, Gawer (2014) proposes a framework focusing on the interaction of innovation and competition along with the features of technical platforms. This framework aims to guide the operational strategies of collaboration, innovation, and competition for technological platforms (Gawer, 2014). Compared with the framework proposed by Gawer (2014), the “3As” framework focuses on uncovering the implementation of advanced technologies in improving platform operations. More specifically, the “3As” framework applies a different platform classification paradigm from Gawer (2014), as we categorize platforms according to functions and sides. Moreover, our “3As” framework differs from those exploring the implementation of advanced technologies in other domains. For instance, Kamble et al. (2018) propose a framework to discuss the applications of Industry 4.0 technologies in achieving sustainable industries. As the focal domains are different, the components of the framework proposed by Kamble et al. (2018) and our “3As” framework are distinct. Kamble et al.’s (2018) framework focuses more on business integration by implementing Industry 4.0 technologies, while the “3As” framework pays more attention to the improvements of operational issues. Finally, the “3As” framework uncovers three developments to improve the “3As” operations in terms of strengthening the activities within components and providing guidance on policymaking.

To demonstrate the value of the proposed “3As” framework, we study how it can be applied in Amazon.com. We choose Amazon.com because it is an industrial giant with lots of public information. As we have conducted a relatively comprehensive case study on Amazon.com (see Appendix A refer to the published paper), in this part, we focus on highlighting the related actions of Amazon.com on the proposed three developments under the “3As” framework.

Collaborations: Amazon.com has adopted the collaboration strategy to help to enhance the sales opportunity and achieve economic outcomes. For instance, the “IoT and big data” collaboration can be witnessed in the use of Alexa in Amazon.com.

Transformations: Amazon.com has initiated the transformation from a standard two-sided PS platform to an n-sided PS platform. Similar to most e-commerce platforms, Amazon.com has launched Amazon Live, the live stream platform of Amazon.com. On this platform, instead of directly being linked with sellers, consumers are connected with influencers who promote products. With the development of livestream shopping, livestream selling will become one of the major features of Amazon.com.

Regulations: The authorities have been closely monitoring large e-commerce enterprises. Under the monitoring, Amazon.com has actively developed operational regulations in platform operations from the aspects of the global selling, consumer privacy protection, tax, and so on.

2. Descriptions of mobile apps for Chanel, Louis Vuitton, H&M, and P&B in App Store.

Functions	Apps	Sources
Using apps to promote products.	CHANEL FASHION	https://apps.apple.com/us/app/chanel-fashion/id409934435
	Louis Vuitton	https://apps.apple.com/us/app/louis-vuitton/id709101942
Using apps to promote and sell products.	PULL&BEAR	https://apps.apple.com/us/app/pull-bear/id388614277
	H&M - we love fashion	https://apps.apple.com/us/app/h-m-we-love-fashion/id834465911

Appendix II Mathematical Proofs

II-A: Mathematical Proofs for Chapter 3

Proof of Proposition 3.1:

Based on the optimal decision Q_R^* and optimal expected profit Π_R^* shown in Chapter 3, we then obtain properties of first order derivatives of the optimal decisions and solutions with respect to l and g , respectively. The results are shown in Table 3.7.

Besides, we check the first order derivatives of the optimal FET adoption level θ_R^* with respect to l and g . We find that θ_R^* is unrelated to l and g . (Q.E.D.)

Proof of Proposition 3.2

Based on the optimal decisions Q_R^* , θ_R^* , and the optimal expected profit Π_R^* shown in Chapter 3, we then can obtain properties of first order derivatives of the optimal decisions and solutions with respect to σ_{MA} and σ_{WS} , respectively. The results are shown in Table 3.8. (Q.E.D.)

Proof of Proposition 3.3

Based on the optimal decisions Q_R^* , θ_R^* , and the optimal expected profit Π_R^* shown in Chapter 3, we then can obtain properties of first order derivatives of the optimal decisions and solutions with respect to α and a , respectively.

$$\frac{\partial Q_R^*}{\partial a} = \frac{1+\lambda}{1-\gamma\lambda} > 0, \quad \frac{\partial \theta_R^*}{\partial a} = 0 \quad \text{and} \quad \frac{\partial Q_R^*}{\partial a} = \frac{1+\lambda}{1-\gamma\lambda};$$
$$\frac{\partial Q_R^*}{\partial \alpha} = \frac{1+\gamma}{1-\gamma\lambda} > 0, \quad \frac{\partial \theta_R^*}{\partial \alpha} = 0, \quad \text{and} \quad \frac{\partial \Pi_R^*}{\partial \alpha} = \frac{1+\gamma}{1-\gamma\lambda}. \quad (\text{Q.E.D.})$$

Proof of Proposition 3.4

(i) When the TT contract is adopted, the retailer undertakes the side-payment Y^{TT} from it to the manufacturer. The manufacturer decides the optimal unit wholesale and side-payment. Similar to approach used in Chapter 3, we derive the optimal ordering quantity for the retailer by solving

$$\Pi_R^{TT}(Q|\theta) = (p-v) \left[\left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right) - \varepsilon(\theta)S \left[\Psi \left(\frac{Q - \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right)}{\varepsilon(\theta)S} \right) \right] \right] - (w-v)Q - K(\theta) - Y^{TT} \quad \text{and}$$

obtaining that the optimal ordering quantity is same as the one in the basic model and corresponding

optimal profit equals $\Pi_R^{TT*} |_{\theta} = (p-w) \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right) - K(\theta) - \varepsilon(\theta)B_R S - Y^{TT}$. Then, letting

$Q_R^{TT*} = Q_{SC}^*$, we obtain the optimal wholesale price $w^{TT*} = c$. Then, solving $\Pi_M^{TT*}(w^{TT*}) = (1-\xi)\Pi_{SC}^*$,

we can obtain $Y^{TT*} = (1-\xi)\Pi_{SC}^*$.

(ii) When PS contract is adopted, the retailer needs to share s^{PS} proportion of its profit to the manufacturer. The unit wholesale price and the proportion of profit share by the retailer is decided by the manufacturer. Similar to the approach used in (i), we can obtain $w^{PS*} = c$ and $s^{PS*} = (1-\xi)$.

(iii) Besides, we derive the settings of the MS contract in the following.

First, we derive that the optimal ordering quantity for the retailer under the MS contract is

$Q_R^{MS*} = \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right) + \varepsilon(\theta_R^{MS*})S\Phi^{-1} \left(\frac{p-w}{p-v-m} \right)$. Second, solving $Q_R^{MS*} = Q_{SC}^*$, we obtain the

optimal markdown sponsor for the manufacturer is $m^{MS*} = \frac{(p-v)(w^{MS*} - c)}{(p-c)}$. Finally, substituting m^{MS*}

into $\Pi_R^{MS*} = (p-w) \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right) - K(\theta_R^{MS*}) - \varepsilon(\theta_R^{MS*})B_R^{MS} S$, where

$B_R^{MS} = (p-v-m)\phi \left[\Phi^{-1} \left(\frac{p-w}{p-v-m} \right) \right]$, we can obtain $\Pi_R^{MS*}(m^{MS*})$. Solving $\Pi_R^{MS*}(m^{MS*}) = \xi\Pi_{SC}^*$, we can

obtain that $w^{MS*} = p - \left(\frac{\xi\Pi_{SC}^* + K(\theta_{SC}^*)}{J - \left(\frac{p-v}{p-c} \right)\varepsilon(\theta_{SC}^*)\phi[\Phi^{-1}(q_{SC}^*)]} \right)$, where $J = \left(\frac{a+\alpha+a\lambda+\alpha\gamma}{1-\lambda\gamma} \right)$.

Overall, the e-commerce supply chain can be coordinated with the contract settings shown in Table 3.9. (Q.E.D.)

Proof of Proposition 3.5

We check the first order derivatives of the optimal contract settings for TT and PS with respect to l and g . We find that the contract settings are unrelated to l and g .

Besides, based on the optimal decisions w_{MS}^* and m_{MS}^* shown in Chapter 3 we then obtain properties of first order derivatives of them with respect to l and g , respectively. The results are shown in Table 3.10b. (Q.E.D.)

Proof of Proposition 3.6

Based on the optimal decision Q_{SC}^* and optimal expected profit Π_{SC}^* shown in Chapter 3, we then obtain properties of first order derivatives of the optimal decisions and solutions with respect to l and g , respectively. The results are shown in Table 3.11. (Q.E.D.)

Please refer to Table 3.11 for the proof of Proposition 3.7 and Corollary 3.1. (Q.E.D.)

Proof of Proposition 3.8

(a) Comparing Eq. (3.7) and Eq. (3.8), we can obtain that $\Pi_R^{\overline{BCT}^*} < \Pi_R^{BCT^*}$ when $T < \overline{T}_R$;

Comparing Eq. (3.10) and Eq. (3.11), we can obtain that $\Pi_{SC}^{\overline{BCT}^*} < \Pi_{SC}^{BCT^*}$ when $T < \overline{T}_{SC}$.

(b) Based on the optimal expected profits $\Pi_R^{\overline{BCT}^*}$, $\Pi_R^{BCT^*}$, $\Pi_{SC}^{\overline{BCT}^*}$, and $\Pi_{SC}^{BCT^*}$, it can be observed implementing supply chain will not affect the first order derivatives of expected profits with respect to l and g . (Q.E.D.)

II-B: Mathematical Proofs for Chapter 4

Linear Price-Dependent Demand Model and Consumer Utility Model:

Consider the case when consumers in the market possess a valuation v towards the product, and v is uniformly distributed between 0 and $A > 0$.

We denote the density function as $\zeta(v)$. The market popular is $N > 0$. Then, under Model DO, the demand is:

$$d_{DO} = N \int_p^A \zeta(v) dv = N \left(\int_0^A \zeta(v) dv - \int_0^p \zeta(v) dv \right) = N(1 - p/A) = N - \frac{Np}{A}.$$

Thus, mapping into the demand function in the main body, we can see that: $a = N$ and $b = \frac{N}{A}$, which means the linear price-dependent demand model is consistent with the commonly seen consumer utility model in the supply chain management literature. (Q.E.D.)

Proof of Corollary 4.1:

We check the first-order derivatives of the optimal prices and proportion of revenue share with respect to channel influences (i.e., λ and l). Table II-1 and Table II-1 summarize the results.

Table II-1. The sensitivity analysis of optimal decisions for Model DP.

	$\lambda \uparrow$	$l \uparrow$
p_{ET}^{DP*}	\uparrow when $a < \bar{a}_1$, and \downarrow when $a > \bar{a}_1$.	If $\lambda + \phi > 0$, \downarrow when $a < \bar{a}_2$, and \uparrow when $a > \bar{a}_2$; If $\lambda + \phi < 0$, \uparrow when $a > \bar{a}_2$, and \downarrow when $a < \bar{a}_2$.
p_{ET}^{DP*}	\uparrow when $a < \bar{a}_3$, and \downarrow when $a > \bar{a}_3$.	\downarrow when $a < \bar{a}_4$, and \uparrow when $a > \bar{a}_4$.

Table II-2. The sensitivity analysis of γ^{DP*} .

	$\lambda \uparrow$	$l \uparrow$
γ^{DP*}	\uparrow when $a < \bar{a}_3$, and \downarrow when $a > \bar{a}_3$.	If $\lambda > 0$ and $l \in [R_1, R_2]$, \downarrow when $a < \bar{a}_3$, and \uparrow when $a > \bar{a}_3$; If $\lambda < 0$ and $l \in [R_1, R_2]$, \uparrow when $a < \bar{a}_3$, and \downarrow when $a > \bar{a}_3$;

The definitions of some terms used in this part are given as follows:

$$\bar{a}_1 = \frac{\beta^2 (w(-l + \phi) + y\phi) + b(\alpha - lw\beta + l(\alpha + (w + y)\beta)\phi)}{\beta + l\beta\phi},$$

$$\begin{aligned} \frac{-}{a_2} &= \frac{b(-w(b+\beta\lambda) + (\alpha\lambda + (w+y)(b+\beta\lambda))\phi + \alpha\phi^2)}{\beta\phi(\lambda+\phi)}, \frac{-}{a_3} = \frac{b(1+l)\alpha + bl(-c+y)\beta + (-c+y)\beta^2}{(1+l)\beta}, \\ \frac{-}{a_4} &= \frac{b(\alpha(1+\lambda) - (c-y)(b+\beta\lambda))}{\beta(1+\lambda)}, R_1 = \frac{b - \sqrt{(1+\lambda)(b+\beta\lambda)^2}}{b\lambda}, R_2 = \frac{b + \sqrt{(1+\lambda)(b+\beta\lambda)^2}}{b\lambda}. \end{aligned}$$

Proof of Proposition 4.1:

Under Model i , for $i \in (PP, DP)$, when the RSF service contract parameter $\gamma = \gamma^*$, we have the e-tailer's optimal pricing decision being the same as the ET-PF system's optimal pricing decision. This is the first incentive alignment. However, this is not flexible and insufficient to allocate the profit between the e-tailer and e-platform.

To have the flexible allocation, we need to set ξ to divide the profit. Note that the e-tailer and e-platform have their own reservation profits of Ω_{ET} and Ω_{PF} , respectively. Thus, we have the following analysis.

Under Model PP, the following must hold:

$$\Pi_{ET}^{PP}(p_{SYS}^{PP*}) = ((1 - \gamma^{PP*})p_{SYS}^{PP*} - w)(\alpha - \beta p_{SYS}^{PP*}) - \xi \geq \Omega_{ET}, \quad (A1)$$

$$\Pi_{PF}^{PP}(p_{SYS}^{PP*}) = (\gamma^{PP*}p_{SYS}^{PP*} - c)(\alpha - \beta p_{SYS}^{PP*}) + \xi \geq \Omega_{PF}. \quad (A2)$$

From (A1) and (A2), we can see that they are the same as

$$\Omega_{PF} - \Omega_{PF}^{PP*} \leq \xi \leq \Omega_{ET}^{PP*} - \Omega_{ET},$$

where $\Omega_{ET}^{PP*} = ((1 - \gamma^{PP*})p_{SYS}^{PP*} - w)(\alpha - \beta p_{SYS}^{PP*})$, and $\Omega_{PF}^{PP*} = (\gamma^{PP*}p_{SYS}^{PP*} - c)(\alpha - \beta p_{SYS}^{PP*})$.

Under Model DP, the following must hold:

$$\Pi_{ET}^{DP}(p_{SYS}^{DP*}) \geq \Omega_{ET}, \quad (A3)$$

$$\Pi_{PF}^{DP}(p_{SYS}^{DP*}) + \xi \geq \Omega_{PF}. \quad (A4)$$

From (A3) and (A4), we can see that they are the same as:

$$\Omega_{PF} - \Omega_{PF}^{DP*} \leq \xi \leq \Omega_{ET}^{DP*} - \Omega_{ET},$$

where

$$\Omega_{ET}^{DP*} = \{(p_{SYS}^{DP*} - w - y)(a - bp_{SYS}^{DP*} + \lambda(\alpha - \beta p_{SYS}^{DP*}) - Z) + \{((1 - \gamma^{DP*})p_{SYS}^{DP*} - w)(\alpha - \beta p_{SYS}^{DP*} + l(a - bp_{SYS}^{DP*}))\}\}$$

,

$$\Omega_{PF}^{DP*} = (\gamma^{DP*}p_{SYS}^{DP*} - c)(\alpha - \beta p_{SYS}^{DP*} + l(a - bp_{SYS}^{DP*})).$$

Proposition 4.1 is proven.

(Q.E.D.)

Proof of Proposition 4.2:

If $\max(\Pi_{SYS}^{PP*}, \Pi_{SYS}^{DP*}) \leq \Pi_{SYS}^{DO*}$, then adopting Model PP or Model DP will never yield a profit higher than adopting Model DO. As a result, the optimal channel choice is DO.

If $\min(\Pi_{SYS}^{PP*}, \Pi_{SYS}^{DP*}) > \Pi_{SYS}^{DO*}$, then adopting Model PP or Model DP will yield a profit higher than adopting Model DO. As a result, the optimal channel choice is to adopt the e-platform which means either Model PP or Model DP. (Q.E.D.)

Explanation of Algorithm 1:

Algorithm 1 is intuitive. From Proposition 4.2, we have Step 1.2. In Stage 2, we compare between Model PP and Model DP and identify the best one from the ET-PF systems perspective. In Stage 3, after having the optimal model determined in Stage 2, we set the respective optimal RSF service contract parameters (using Proposition 4.1). Finally, we determine the optimal product selling price with respect to the optimal RSF service contract parameters under the optimal channel choice model by using the analytical results derived in Chapter 4.2. (Q.E.D.)

Proof of Proposition 4.3:

Under Model DO with the sales rebate contract: If the product supply chain includes a separate upstream manufacturer and an e-tailer, the profit functions of the manufacturer (MU) and the e-tailer are given below (P.S.: We add a \sim to represent the function and optimal decisions under this extended analysis):

$$\tilde{\Pi}_{ET}^{DO} = ((1+r)p - g - y)(a - bp) - Z, \quad (A5)$$

$$\tilde{\Pi}_{MU}^{DO} = (rp + g - w)(a - bp). \quad (A6)$$

For the e-tailer, for given r and g , the optimal product price is found by the first-order condition because

$\tilde{\Pi}_{ET}^{DO}$ is concave:

$$\frac{d\tilde{\Pi}_{ET}^{DO}}{dp} = 0 \text{ implies } \tilde{p}_{ET}^{DO*} = \frac{a(1+r) + b(y+g)}{2b(1+r)}. \quad (A7)$$

The optimal product ET-MU supply chain's product selling price is:

$$\tilde{p}_{ET+MU}^{DO*} = \frac{a}{2b} + \frac{w+y}{2}. \quad (A8)$$

Observing that:

$$\tilde{p}_{ET}^{DO*} = \tilde{p}_{ET+MU}^{DO*} \Leftrightarrow g = (1+r)w. \quad (A9)$$

Thus, from (A9), we have: Under a SR contract, the product supply chain can be internally coordinated by setting $g=(I+r)w$ and different (g, r) pairs will yield different profit divisions between the manufacturer and e-tailer.

The same logic applies to Model PP and Model DP for the product supply chain part. Obviously, this extension does not affect the detailed optimization algorithm as shown in Algorithm 1 provided that the product ET-MU supply chain can be internally coordinated, e.g., by the SR contract.(Q.E.D.)

Proof of Proposition 4.4:

If $\max (CS_{SYS}^{PP}, CS_{SYS}^{DP}) \leq CS_{SYS}^{DO}$ and $\max (\Pi_{SYS}^{PP*}, \Pi_{SYS}^{DP*}) \leq \Pi_{SYS}^{DO*}$, then adopting Model PP or Model DP will never yield both the profit and consumer surplus higher than adopting Model DO. As a result, the optimal channel choice is DO. If $\min(CS_{SYS}^{PP}, CS_{SYS}^{DP}) > CS_{SYS}^{DO}$ and $\min (\Pi_{SYS}^{PP*}, \Pi_{SYS}^{DP*}) > \Pi_{SYS}^{DO*}$, then adopting Model PP or Model DP will yield both the profit higher and consumer surplus higher than adopting Model DO. As a result, the optimal channel choice is to adopt the e-platform which means either Model PP or Model DP. (Q.E.D.)

Proof of Proposition 4.5:

Under Model i , for $i \in (PP, DP)$, when the RSF contract parameters meet the condition $\gamma = \gamma_{SW}^{i*}$, we can show that the optimal pricing decision of e-tailer being the same as the optimal pricing decision of the ET-PF system. As a result, the first “incentive alignment” of social welfare optimization is achieved. After that, we need to set ξ to allocate the systems benefit between the e-tailer and e-platform based on their “reservation social welfares” (RSWs), i.e., Ω_{ET}^{SW} and Ω_{PF}^{SW} , respectively. In order to examine the value of ξ to optimize social welfare, we conduct the following analysis.

Under Model PP, the social welfare for each agent should be larger than or equal to its own RSW.

$$SW_{ET}^{PP}(p_{SYS}^{PP,SW*}) = h\left(\frac{1}{2}d_{PP}(\bar{p}_{PP} - p_{SYS}^{PP,SW*})\right) + (1-h)\{((1-\gamma^{PP*})p_{SYS}^{PP,SW*} - w)(\alpha - \beta p_{SYS}^{PP,SW*}) - \xi\} \geq \Omega_{ET}^{SW}, \quad (A10)$$

$$SW_{PF}^{PP}(p_{SYS}^{PP,SW*}) = h\left(\frac{1}{2}d_{PP}(\bar{p}_{PP} - p_{SYS}^{PP,SW*})\right) + (1-h)\{(\gamma^{PP*}p_{SYS}^{PP,SW*} - c)(\alpha - \beta p_{SYS}^{PP,SW*}) + \xi\} \geq \Omega_{PF}^{SW}. \quad (A11)$$

From (A10) and (A11), it can be derived that $\frac{\Omega_{PF}^{SW}}{1-h} - \Omega_{PF}^{PP,SW*} \leq \xi \leq \Omega_{ET}^{PP,SW*} - \frac{\Omega_{ET}^{SW}}{1-h}$, in which

$$\Omega_{ET}^{PP,SW*} = \frac{h}{1-h}\left(\frac{1}{2}d_{PP}(\bar{p}_{PP} - p_{SYS}^{PP,SW*})\right) + ((1-\gamma^{PP*})p_{SYS}^{PP,SW*} - w)(\alpha - \beta p_{SYS}^{PP,SW*}) \quad \text{and}$$

$$\Omega_{PF}^{PP,SW*} = \frac{h}{1-h}\left(\frac{1}{2}d_{PP}(\bar{p}_{PP} - p_{SYS}^{PP,SW*})\right) + (\gamma^{PP*}p_{SYS}^{PP,SW*} - c)(\alpha - \beta p_{SYS}^{PP,SW*}).$$

Under Model DP, the social welfare for each agent should be larger than or equal to its own RSW as well, and the following should hold:

$$SW_{ET}^{DP}(p_{SYS}^{DP,SW*}) = h\left(\frac{1}{2}d_{DP}(p_{SYS}^{DP,SW*})(\bar{p}_{DP} - p_{SYS}^{DP,SW*})\right) + (1-h)\{(p_{SYS}^{DP,SW*} - w - y)(a - bp_{SYS}^{DP,SW*} + \lambda(\alpha - \beta p_{SYS}^{DP,SW*})) - Z\} \\ + (1-h)\{(\phi p_{SYS}^{DP,SW*} - w)(\alpha - \beta p_{SYS}^{DP,SW*} + l(a - bp_{SYS}^{DP,SW*})) - \xi\} \geq \Omega_{ET}^{SW}, \quad (A12)$$

$$SW_{PF}^{DP}(p_{SYS}^{DP,SW*}) = h\left(\frac{1}{2}((\alpha - \beta p + l(a - bp_{SYS}^{DP,SW*}))) (\bar{p}_{PP} - p_{SYS}^{DP,SW*})\right) \\ + (1-h)\{(\gamma^{DP*} p_{SYS}^{DP,SW*} - c)(\alpha - \beta p + l(a - bp_{SYS}^{DP,SW*})) + \xi\} \geq \Omega_{PF}^{SW}. \quad (A13)$$

From (A12) and (A13), we can see that $\frac{\Omega_{PF}^{SW}}{1-h} - \Omega_{PF}^{DP,SW*} \leq \xi \leq \Omega_{ET}^{DP,SW*} - \frac{\Omega_{ET}^{SW}}{1-h}$,

where

$$\Omega_{ET}^{DP,SW*} = \frac{h}{1-h}\left(\frac{1}{2}d_{DP}(p_{SYS}^{DP,SW*})(\bar{p}_{DP} - p_{SYS}^{DP,SW*})\right) + \{(p_{SYS}^{DP,SW*} - w - y)(a - bp_{SYS}^{DP,SW*} + \lambda(\alpha - \beta p_{SYS}^{DP,SW*})) - Z\} \\ + \{(\phi p_{SYS}^{DP,SW*} - w)(\alpha - \beta p_{SYS}^{DP,SW*} + l(a - bp_{SYS}^{DP,SW*}))\} \geq \Omega_{ET}^{SW},$$

$$\Omega_{PF}^{DP,SW*} = \frac{h}{1-h}\left(\frac{1}{2}((\alpha - \beta p + l(a - bp_{SYS}^{DP,SW*}))) (\bar{p}_{PP} - p_{SYS}^{DP,SW*})\right) + \{(\gamma^{DP*} p_{SYS}^{DP,SW*} - c)(\alpha - \beta p + l(a - bp_{SYS}^{DP,SW*}))\}.$$

Proposition 4.5 is proven. (Q.E.D.)

Proof of Corollary 4.1:

(i) The consumer surplus functions are shown as follows:

$$\text{Under Model DO: } CS_{SYS}^{DO} = CS_{ET}^{DO} = \frac{(a - b(w + y))^2}{8b};$$

$$\text{Under Model PP: } CS_{SYS}^{PP} = \frac{(\alpha - \beta(c + w))^2}{8\beta};$$

$$\text{Under Model DP: } CS_{SYS}^{DP} = \frac{(a(1+l) - b(w + l(c + w) + y) + \alpha(1+l) - \beta(c + w + (w + y)\lambda))^2}{8(b + bl + \beta + \beta\lambda)}.$$

(ii) In order to avoid trivial cases, we impose a symmetry assumption that $a = \alpha$ and $b = \beta$. It means we ignore the effect of differences of market base between Model DO and Model PP, as well as the effect of demand sensitivity of price.

(iii) By comparing consumer surplus under Model DO with consumer surplus of the other two models, we can obtain that:

a. $CS_{SYS}^{DO} > CS_{SYS}^{PP}$ if $c > y$;

b. $CS_{SYS}^{PP} > CS_{SYS}^{DP}$ if $\lambda + \lambda^2 > 1 + l$ and $y \in [y_1, y_2]$, or $\lambda + \lambda^2 \leq 1 + l$ and $y \in [y_2, y_1]$,

in which, $y_1 = \frac{-\alpha V(1+l+\lambda Z) + \beta(wV(1+l+\lambda Z) + c(1+l)(V+Z+\lambda Z))}{\beta Z(1+l-\lambda(1+\lambda))}$ and

$$y_2 = \frac{\alpha V(1+l-\lambda Z) + \beta(-wV(1+l-\lambda Z) - c(1+l)(V-Z-\lambda Z))}{\beta Z(1+l-\lambda(1+\lambda))}, \text{ where } V = (2+l+\lambda), Z = \sqrt{2+l+\lambda}.$$

Hence, we have $CS_{SYS}^{DO} > CS_{SYS}^{PP} > CS_{SYS}^{DP}$ when $c > y$ and $y \in [\min\{y_1, y_2\}, \max\{y_1, y_2\}]$. (Q.E.D.)

Proof of Proposition 4.6:

If the e-tailer makes decisions on both the retail product price and product quality: (a) The RSF service contract will fail to achieve robust systems optimization contract under both Model \hat{i} , for $i \in (PP, DP)$ because there are two decision and hence two equations. As the fixed service fee can only help allocate profit but cannot affect the optimal pricing and product quality decisions, the RSF contract does not have enough degree of control to help achieve robust systems optimization. With the cost sharing parameter, an additional control is present which helps to achieve robust systems optimization. (Q.E.D.)

Concavity of objective functions in Chapter 4.5.1:

Under Model QDO:

From (4.26), we have: $\Pi_{ET}^{QDO}(p, q) = (p - w - y)(a - bp + fq) - Z - C(q)$. The Hessian matrix is:

$$H_{ET}^{QDO} = \begin{vmatrix} -2b & f \\ f & -\sigma \end{vmatrix}. \text{ Thus, } \Pi_{ET}^{QDO}(p, q) \text{ is concave in } p \text{ and } q \text{ if } \sigma > f^2 / (2b).$$

Under Model QPP:

From (4.29), we have: $\Pi_{ET}^{QPP} = (\phi p - w)(\alpha - \beta p + q) - \xi - C(q)$, and the respective Hessian matrix is:

$$H_{ET}^{QPP} = \begin{vmatrix} -2\beta\phi & \phi \\ \phi & -\sigma \end{vmatrix}.$$

Thus, $\Pi_{ET}^{ODO}(p,q)$ is concave in p and q if $\sigma > \phi / (2\beta)$ for all $\phi \leq 1$ (since $\phi > 0$).

For the ET-PF system, $\Pi_{SYS}^{QPP} = \Pi_{ET}^{QPP} + \Pi_{PF}^{QPP}$ and the respective Hessian matrix is: $H_{SYS}^{QPP} = \begin{vmatrix} -2\beta & 1 \\ 1 & -\sigma \end{vmatrix}$.

Thus, $\Pi_{ET}^{ODO}(p,q)$ is concave in p and q if $\sigma > 1 / (2\beta)$.

Under Model QDD:

From (6.22), we have:

$$\Pi_{ET}^{QDP} = \{(p-w-y)(a-bp+fq+\lambda(\alpha-\beta p+q)-Z)\} + \{(\phi p-w)(\alpha-\beta p+q+l(a-bp+fq))-\xi\} - C(q),$$

the corresponding Hessian matrix is:

$$H_{ET}^{QDP} = \begin{vmatrix} -2(b+\lambda\beta+\phi(\beta+bl)) & (1+l\phi)f+\phi+\lambda \\ (1+l\phi)f+\phi+\lambda & -\sigma \end{vmatrix}.$$

Thus, if $\sigma > \frac{[(1+l\phi)f+\phi+\lambda]^2}{2(b+\lambda\beta+\phi(\beta+bl))}$, then Π_{ET}^{QDP} is concave in p and q .

$$\Pi_{SYS}^{DP} = \Pi_{ET}^{QDP} + \Pi_{PF}^{QDP}.$$

$$H_{SYS}^{QDP} = \begin{vmatrix} -2(b+\lambda\beta+\beta+bl) & (1+l)f+1+\lambda \\ (1+l)f+1+\lambda & -\sigma \end{vmatrix}.$$

Thus, if $\sigma > \frac{[(1+l)f+1+\lambda]^2}{2(b+\lambda\beta+\beta+bl)}$, then Π_{SYS}^{DP} is concave in p and q . (Q.E.D.)

II-C: Mathematical Proofs for Chapter 5

Proof of Proposition 5.1: We first can obtain the optimal profits for Tactic TL and Tactic TF. Then, it is straightforward to obtain the profit difference between them is

$$\Delta \Pi^{C-f} = \Pi^{C-TL}(\xi_L^{C-TL*}) - \Pi^{C-TF}(\xi_F^{C-TF*}) = \frac{(p-c)^2 \left((1+\beta)^2 \phi_L^2 - (1-\lambda)^2 \phi_F^2 \right)}{2k(1+\beta\lambda)^2}. \text{ Based on it, we derive}$$

$$\Delta \Pi^{C-f} > 0 \text{ if and only if } \frac{\phi_L}{\phi_F} > \left| \frac{1-\lambda}{1+\beta} \right|, \text{ and } \Delta \Pi^{C-f} \leq 0 \text{ if and only if } \frac{\phi_L}{\phi_F} < \left| \frac{1-\lambda}{1+\beta} \right|.$$

Moreover, the constraint $\frac{\phi_L}{\phi_F} > \left| \frac{1-\lambda}{1+\beta} \right|$ (resp. $\frac{\phi_L}{\phi_F} < \left| \frac{1-\lambda}{1+\beta} \right|$) can be expressed as

$$\max \left\{ 0, 1 - \frac{(1+\beta)\phi_L}{\phi_F} \right\} < \lambda < 1 + \frac{(1+\beta)\phi_L}{\phi_F} \text{ (resp. } \lambda > 1 + \frac{(1+\beta)\phi_L}{\phi_F} \text{).} \quad (\text{Q.E.D.})$$

Proof of Proposition 5.2: Substituting optimal advertising levels into objectives, we can derive the optimal profits for the NPM and PM (i.e., Tactic TL and Tactic TF) scenarios respectively. Then, comparing the two polarized tactics with the NPM scenario respectively. We can generate the following findings.

(i) Comparing profits between TL and NPM, it is straightforward to obtain

$$\Pi^{C-TL}(\xi_L^{C-TL*}) - \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) = \widehat{F} - \frac{(p-c)^2 (1-\lambda)^2 \phi_F^2}{2k(1+\beta\lambda)^2}, \text{ and we can get}$$

$$\Pi^{C-TL}(\xi_L^{C-TL*}) > \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) \text{ if and only if } \widehat{F} > \widehat{F}_L = \frac{(p-c)^2 (1-\lambda)^2 \phi_F^2}{2k(1+\beta\lambda)^2}.$$

(ii) Comparing profits between TF and NPM, it is straightforward to obtain

$$\Pi^{C-TF}(\xi_F^{C-TF*}) - \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) = \widehat{F} - \frac{(p-c)^2 (1+\beta)^2 \phi_L^2}{2k(1+\beta\lambda)^2}, \text{ and we can get}$$

$$\Pi^{C-TF}(\xi_F^{C-TF*}) > \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) \text{ if and only if } \widehat{F} > \widehat{F}_F = \frac{(p-c)^2 (1+\beta)^2 \phi_L^2}{2k(1+\beta\lambda)^2}.$$

In summary, only when $\widehat{F} > \max\{\widehat{F}_L, \widehat{F}_F\}$ is satisfied, the PM scenario will be optimal for the LFB.

(Q.E.D.)

Proof of Proposition 5.3: Substituting the optimal advertising levels into objectives under different cases, we can obtain the optimal profits. Then, we compare profits between sub-cases (i.e., the NPM scenario, TL Tactic, and TF Tactic) of the customized advertising strategy and the non-customized advertising strategy one by one.

(i) Comparing the NPM scenario and the non-customized advertising strategy, it can be obtained that

$$\Pi^{NC}(\xi^{NC*}) - \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) = 2\widehat{F} - \frac{(p-c)^2(1+\beta)(\lambda-1)\phi_L\phi_F}{k(1+\beta\lambda)^2}. \text{ Then, we can get}$$

$$\Pi^{NC}(\xi^{NC*}) < \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) \quad \text{if and only if} \quad \lambda > \lambda_1 = 1 \quad \text{and}$$

$$\widehat{F} < \widehat{F}_1 = \frac{(p-c)^2(1+\beta)(\lambda-1)\phi_L\phi_F}{2k(1+\beta\lambda)^2}.$$

(ii) Comparing Tactic TL and the non-customized advertising strategy, we have

$$\Pi^{NC}(\xi^{NC*}) - \Pi^{C-TL}(\xi_L^{C-TL*}) = \widehat{F} - \frac{(p-c)^2(\lambda-1)\phi_F(2(1+\beta)\phi_L + (1-\lambda)\phi_F)}{2k(1+\beta\lambda)^2}. \text{ Then, we can get}$$

$$\Pi^{NC}(\xi^{NC*}) < \Pi^{C-TL}(\xi_L^{C-TL*}) \quad \text{if and only if} \quad 1 = \lambda_1 < \lambda < \lambda_2 = 1 + \frac{2(1+\beta)\phi_L}{\phi_F} \quad \text{and}$$

$$\widehat{F} < \widehat{F}_2 = \frac{(p-c)^2(\lambda-1)\phi_F(2(1+\beta)\phi_L + (1-\lambda)\phi_F)}{2k(1+\beta\lambda)^2}.$$

(iii) Comparing Tactic TF and the non-customized advertising strategy, it can be obtained that

$$\Pi^{NC}(\xi^{NC*}) - \Pi^{C-TF}(\xi_F^{C-TF*}) = \widehat{F} + \frac{(p-c)^2(1+\beta)\phi_L((1+\beta)\phi_L + 2(1-\lambda)\phi_F)}{2k(1+\beta\lambda)^2}. \text{ Then, we can get}$$

$$\Pi^{NC}(\xi^{NC*}) < \Pi^{C-TF}(\xi_F^{C-TF*}) \quad \text{if and only if} \quad \lambda > \lambda_3 = 1 + \frac{(1+\beta)\phi_L}{2\phi_F} \quad \text{and}$$

$$\widehat{F} < \widehat{F}_3 = -\frac{(p-c)^2(1+\beta)\phi_L((1+\beta)\phi_L + 2(1-\lambda)\phi_F)}{2k(1+\beta\lambda)^2}.$$

In short, it is identified that the optimal implementation of advertising strategy depends on λ and \widehat{F} . We find that the thresholds of λ satisfy the following size relationship $\lambda_1 < \lambda_3 < \lambda_2$. Therefore, the optimal advertising strategy can be derived, depending on how \widehat{F} appears in different intervals of λ .

(a) For $\lambda \in (0, \lambda_1)$, $\Pi^{NC}(\xi^{NC*}) > \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})$ always holds.

(b) For $\lambda \in (1, \lambda_3)$, $\Pi^{C-TF}(\xi_F^{C-TF*})$ will not be the optimal solution. Then, the relationship among

$\Pi^{NC}(\xi^{NC*})$, $\Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})$, and $\Pi^{C-TL}(\xi_L^{C-TL*})$ depends on \widehat{F} . When $\lambda \in (1, \lambda_3)$,

we can obtain $\widehat{F}_2 > \widehat{F}_1 > \widehat{F}_L > 0$. That is to say,

$\Pi^{NC}(\xi^{NC*}) > \max\{\Pi^{C-TL}(\xi_L^{C-TL*}), \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})\}$ for $\widehat{F} > \widehat{F}_2$;

$\Pi^{C-TL}(\xi_L^{C-TL*}) > \max\{\Pi^{NC}(\xi^{NC*}), \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})\}$ for $\widehat{F}_L < \widehat{F} < \widehat{F}_2$;

$\Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) > \max\{\Pi^{NC}(\xi^{NC*}), \Pi^{C-TL}(\xi_L^{C-TL*})\}$ for $0 < \widehat{F} < \widehat{F}_L$.

(c) For $\lambda \in (\lambda_3, \lambda_2)$, four cases would be the optimal strategy, which depends on \widehat{F} . In this case,

relationships among \widehat{F}_1 , \widehat{F}_2 , and \widehat{F}_3 differs in the intervals $\lambda \in (\lambda_3, 1 + \frac{(1+\beta)\phi_L}{\phi_F})$ and

$\lambda \in (1 + \frac{(1+\beta)\phi_L}{\phi_F}, \lambda_2)$. Specifically,

a) if $\lambda \in (\lambda_3, 1 + \frac{(1+\beta)\phi_L}{\phi_F})$, there is $\widehat{F}_2 > \widehat{F}_1 > \widehat{F}_3$ and $\widehat{F}_2 > \widehat{F}_F > \widehat{F}_1 > \widehat{F}_L > \widehat{F}_3$. That is to say,

$\Pi^{NC}(\xi^{NC*})$ is optimal when $\widehat{F} > \widehat{F}_2$; $\Pi^{C-TL}(\xi_L^{C-TL*})$ is optimal when $\widehat{F}_2 > \widehat{F} > \widehat{F}_L$;

$\Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})$ is optimal when $\widehat{F}_L > \widehat{F} > 0$.

b) if $\lambda \in (1 + \frac{(1+\beta)\phi_L}{\phi_F}, \lambda_2)$, there is $\widehat{F}_3 > \widehat{F}_1 > \widehat{F}_2$ and $\widehat{F}_L > \widehat{F}_3 > \widehat{F}_1 > \widehat{F}_F > \widehat{F}_2$. That is to say,

$\Pi^{NC}(\xi^{NC*})$ is optimal when $\widehat{F} > \widehat{F}_3$; $\Pi^{C-TF}(\xi_F^{C-TF*})$ is optimal when $\widehat{F}_3 > \widehat{F} > \widehat{F}_F$;

$\Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})$ is optimal when $\widehat{F}_F > \widehat{F} > 0$.

(d) For $\lambda \in (\lambda_2, \infty)$, $\Pi^{C-TL}(\xi_L^{C-TL*})$ will not be the optimal solution. Then, the relationships among

$\Pi^{NC}(\xi^{NC*})$, $\Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})$, and $\Pi^{C-TF}(\xi_F^{C-TF*})$ depends on \widehat{F} . When

$\lambda \in (\lambda_2, \infty)$, we can obtain $\widehat{F}_3 > \widehat{F}_1 > \widehat{F}_F > 0$. That is to say,

$\Pi^{NC}(\xi^{NC*}) > \max\{\Pi^{C-TF}(\xi_F^{C-TF*}), \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})\}$ for $\widehat{F} > \widehat{F}_3$;

$\Pi^{C-TF}(\xi_F^{C-TF*}) > \max\{\Pi^{NC}(\xi^{NC*}), \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})\}$ for $\widehat{F}_F < \widehat{F} < \widehat{F}_3$;

$$\Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) > \max\{\Pi^{NC}(\xi^{NC*}), \Pi^{C-TF}(\xi_F^{C-TF*})\} \text{ for } 0 < \widehat{F} < \widehat{F}_F.$$

In summary, the optimal advertising strategy can be generated. (Q.E.D.)

Proof of Proposition 5.4: We can derive the first-order derivatives of optimal advertising levels w.r.t. λ .

(i) Under the NPM scenario, we can obtain $\frac{\partial \xi_L^{C-NPM*}}{\partial \lambda} = -\frac{k(p-c)\beta(1+\beta)\phi_L}{(k+k\beta\lambda)^2} < 0$ and $\xi_L^{C-NPM*} > 0$

always hold. In addition, $\frac{\partial \xi_F^{C-NPM*}}{\partial \lambda} = -\frac{(p-c)(1+\beta)\phi_F}{k(1+\beta\lambda)^2} < 0$, and $\xi_F^{C-NPM*} > 0$ if and only if $\lambda < 1$ can be obtained.

(ii) Under the TL and TF tactics, the first-order derivatives of the optimal advertising levels w.r.t. λ for the targeted groups are equal to the NPM scenario.

(iii) Under the non-customized advertising strategy, we can obtain $\frac{\partial \xi^{NC*}}{\partial \lambda} = -\frac{(p-c)(1+\beta)(\beta\phi_L + \phi_F)}{k(1+\beta\lambda)^2} < 0$.

Then $\xi^{NC*} > 0$ when $\lambda < 1 + \frac{(1+\beta)\phi_L}{\phi_F}$ and $\xi^{NC*} < 0$ when $\lambda > 1 + \frac{(1+\beta)\phi_L}{\phi_F}$ can be obtained.

In summary, the positivity and negativity of the optimal advertising levels under different cases are provided in Proposition 5.4. (Q.E.D.)

Proof of Proposition 5.5: Note that, to explore the value of implementing negative publicity, we first derive the profits of cases where the negative publicity scheme is the optimal scheme and the negative advertising level is set to be zero (i.e., $\Pi^{t-j/f}(\xi^- = 0)$). Then, we define the difference between the optimal profits and $\Pi^{t-j/f}(\xi^- = 0)$ as $\Delta\Pi_{VN}^{t-j/f}$.

Under the NPM scenario,

$$\Delta\Pi_{VN}^{C-NPM} = \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) - \Pi^{C-NPM}(\xi^- = 0) = \frac{(p-c)^2(1-\lambda)^2\phi_F^2}{2k(1+\beta\lambda)^2}.$$

For the TF tactic of PM scenario, $\Delta\Pi_{VN}^{C-TF} = \Pi^{C-TF}(\xi_F^{C-TF*}) - \Pi^{C-TF}(\xi^- = 0) = \frac{(p-c)^2(1-\lambda)^2\phi_F^2}{2k(1+\beta\lambda)^2}$.

Under the non-customized advertising strategy, we have

$$\Delta\Pi_{VN}^{NC} = \Pi^{NC}(\xi^*) - \Pi^{NC}(\xi^- = 0) = \frac{(p-c)^2((1+\beta)\phi_L + (1-\lambda)\phi_F)^2}{2k(1+\beta\lambda)^2}.$$

According to the above differences, it can be derived that (i) $\Delta\Pi_{VN}^{C-NPM} = \Delta\Pi_{VN}^{C-TF}$ and (ii)

$$\Delta\Pi_{VN}^{NC} < \Delta\Pi_{VN}^{C-NPM} = \Delta\Pi_{VN}^{C-TF} \text{ when } \lambda > 1 + \frac{(1+\beta)\phi_L}{\phi_F}. \quad (\text{Q.E.D.})$$

Proof of Proposition 5.6: Without social influences, we substitute the new demand functions into the objective functions of the customized advertising and non-customized advertising strategy. Then, the optimal advertising levels and the optimal profits can be derived. The optimal advertising levels for different cases are provided in Table II-3. We denote the case without social influence by adding a bar on top of the mathematical notation.

Table II-3. Optimal advertising levels and profits for cases without social influences.

Advertising Strategy		$\bar{\xi}_L$	$\bar{\xi}_F$	$\bar{\Pi}(\xi^*)$
Customized advertising strategy	NPM	$\frac{(p-c)\phi_L}{k}$	$\frac{(p-c)\phi_F}{k}$	$\frac{-2k(c+F_b+cn)+2k(1+2c+n)p - 4kp^2 - 4k\hat{F} + (p-c)^2(\phi_L^2 + \phi_F^2)}{2k}$
	TL	$\frac{(p-c)\phi_L}{k}$	/	$\frac{-2k(c+F_b+\hat{F}+cn)+2k(1+2c+n)p - 4kp^2 + (p-c)^2\phi_L^2}{2k}$
	TF	/	$\frac{(p-c)\phi_F}{k}$	$\frac{-2k(c+F_b+\hat{F}+cn)+2k(1+2c+n)p - 4kp^2 + (p-c)^2\phi_F^2}{2k}$
Non-customized advertising strategy (NC)		$\frac{(p-c)(\phi_L + \phi_F)}{k}$		$\frac{-2k(c+F_b+cn)+2k(1+2c+n)p - 4kp^2 + (p-c)^2(\phi_L + \phi_F)^2}{2k}$

Based on the optimal profits, we conduct comparisons among different cases in the following.

(i) Comparing two polarized segmentation scenarios, we obtain

$$\bar{\Pi}^{C-TL}(\bar{\xi}_L^{C-TL*}) - \bar{\Pi}^{C-TF}(\bar{\xi}_F^{C-TF*}) = \frac{(p-c)^2(\phi_L^2 - \phi_F^2)}{2k}, \text{ and } \bar{\Pi}^{C-TL}(\bar{\xi}_L^{C-TL*}) - \bar{\Pi}^{C-TF}(\bar{\xi}_F^{C-TF*}) > 0 \text{ if and}$$

only if $\phi_L > \phi_F$; and vice versa.

(ii) Comparing the two tactics of PM with the NPM scenario respectively, we obtain the differences shown as follows.

First, it can be calculated that $\bar{\Pi}^{C-TL}(\bar{\xi}_L^{C-TL*}) - \bar{\Pi}^{C-NPM}(\bar{\xi}_L^{C-NPM*}, \bar{\xi}_F^{C-NPM*}) = \hat{F} - \frac{(p-c)^2\phi_F^2}{2k}$, and this value is positive if and only if $\hat{F} > \frac{(p-c)^2\phi_F^2}{2k}$. Second, it can be derived that $\bar{\Pi}^{C-TF}(\bar{\xi}_F^{C-TF*}) - \bar{\Pi}^{C-NPM}(\bar{\xi}_L^{C-NPM*}, \bar{\xi}_F^{C-NPM*}) = \hat{F} - \frac{(p-c)^2\phi_L^2}{2k}$, and this value is positive if and only if $\hat{F} > \frac{(p-c)^2\phi_L^2}{2k}$. In summary, $\min\{\bar{\Pi}^{C-TL}(\bar{\xi}_L^{C-TL*}), \bar{\Pi}^{C-TF}(\bar{\xi}_F^{C-TF*})\} > \bar{\Pi}^{C-NPM}(\bar{\xi}_L^{C-NPM*}, \bar{\xi}_F^{C-NPM*})$ if and only if $\hat{F} > \max\{\frac{(p-c)^2\phi_L^2}{2k}, \frac{(p-c)^2\phi_F^2}{2k}\}$ can be obtained.

(iii) Then, we compare profits between sub-cases (i.e., NPM, TL, and TF) of the customized advertising strategy and the non-customized advertising strategy one by one. Through derivation, we can obtain $\bar{\Pi}^{NC}(\bar{\xi}^{NC*}) > \max\{\bar{\Pi}^{C-TL}(\bar{\xi}_L^{C-TL*}), \bar{\Pi}^{C-TF}(\bar{\xi}_F^{C-TF*}), \bar{\Pi}^{C-NPM}(\bar{\xi}_L^{C-NPM*}, \bar{\xi}_F^{C-NPM*})\}$.

In summary, Proposition 5.6 can be proven. (Q.E.D.)

For the endogenously pricing case, the optimal decisions are advertising level(s) and price, which can be derived by maximizing the LFB's profit. By using the same approach used in the basic model, we summarize the optimal decisions for different cases as following Table II-4 (a) and (b).

Table II-4(a). Optimal decisions under the customized advertising strategy when pricing endogenously.

Scenarios	ξ_L^*	ξ_F^*	p^*
NPM	$\frac{(1-c)(1+\beta)(2+\beta-\lambda)\phi_L}{2k(2+\beta-\lambda)(1+\beta\lambda)-(1+\beta)^2\phi_L^2-(-1+\lambda)^2\phi_F^2}$	$\frac{(1-c)(2+\beta-\lambda)(1-\lambda)\phi_F}{2k(2+\beta-\lambda)(1+\beta\lambda)-(1+\beta)^2\phi_L^2-(-1+\lambda)^2\phi_F^2}$	$\frac{(1+c)k(2+\beta-\lambda)(1+\beta\lambda)-c(1+\beta)^2\phi_L^2-c(1-\lambda)^2\phi_F^2}{2k(2+\beta-\lambda)(1+\beta\lambda)-(1+\beta)^2\phi_L^2-(1-\lambda)^2\phi_F^2}$
TL	$\frac{(1-c)(1+\beta)(2+\beta-\lambda)\phi_L}{2k(2+\beta-\lambda)(1+\beta\lambda)-(1+\beta)^2\phi_L^2}$	/	$\frac{(1+c)k(2+\beta-\lambda)(1+\beta\lambda)-c(1+\beta)^2\phi_L^2}{2k(2+\beta-\lambda)(1+\beta\lambda)-(1+\beta)^2\phi_L^2}$
TF	/	$\frac{(1-c)(2+\beta-\lambda)(1-\lambda)\phi_F}{2k(2+\beta-\lambda)(1+\beta\lambda)-(1-\lambda)^2\phi_F^2}$	$\frac{(1+c)k(2+\beta-\lambda)(1+\beta\lambda)-c(1-\lambda)^2\phi_F^2}{2k(2+\beta-\lambda)(1+\beta\lambda)-(1-\lambda)^2\phi_F^2}$

Table II-4 (b). Optimal decisions under the non-customized advertising strategy when pricing endogenously.

Advertising strategy	ξ^*	p^*
NC	$\frac{(1-c)(2+\beta-\lambda)((1+\beta)\phi_1+(1-\lambda)\phi_2)}{2k(2+\beta-\lambda)(1+\beta\lambda)-((1+\beta)\phi_1+(1-\lambda)\phi_2)^2}$	$\frac{(1+c)k(2+\beta-\lambda)(1+\beta\lambda)-c((1+\beta)\phi_1+(1-\lambda)\phi_2)^2}{2k(2+\beta-\lambda)(1+\beta\lambda)-((1+\beta)\phi_1+(1-\lambda)\phi_2)^2}$

Note that, to ensure the concavity of these four cases (i.e., the negative definite of Hessian Matrix), we have the following constraints: $2k(2+\beta-\lambda)(1+\beta\lambda)-((1+\beta)^2\phi_L^2+(1-\lambda)^2\phi_F^2)=H_1>0$, $2k(2+\beta-\lambda)(1+\beta\lambda)-(1+\beta)^2\phi_L^2=H_2>0$, $2k(2+\beta-\lambda)(1+\beta\lambda)-(1-\lambda)^2\phi_F^2=H_3>0$, and $2k(2+\beta-\lambda)(1+\beta\lambda)-((1+\beta)\phi_L+(1-\lambda)\phi_F)^2=H_4>0$ for the NPM scenario, Tactic TL, Tactic TF, and the non-customized advertising, respectively. Considering these four constraints, it can be found that the intersection of them is $k>\max\{k_{NC}^{EP}, k_{NPM}^{EP}\}$ and $0<\lambda<2+\beta$, where $k_{NPM}^{EP}=\frac{((1+\beta)\phi_L-(\lambda-1)\phi_F)^2}{2(2+\beta-\lambda)(1+\beta\lambda)}$ and $k_{NC}^{EP}=\frac{(1+\beta)^2\phi_L^2+(\lambda-1)^2\phi_F^2}{2(2+\beta-\lambda)(1+\beta\lambda)}$. Under these constraints, $\forall H\in[H_1, H_2, H_3, H_4]$, $H>0$.

Proof of Proposition 5.7: Sensitive analyses of the optimal price w.r.t. social influences λ and β are provided in Table II-5.

Table II-5. Sensitive analysis of the optimal price.

Advertising strategy	$\frac{\partial p^*}{\partial \phi_L}$	$\frac{\partial p^*}{\partial \phi_F}$	$\frac{\partial p^*}{\partial \phi_L \phi_F}$
NPM	+	+	+
TL	+	0	0
TF	0	+	0
NC	+ when $0 < \lambda < \min\{1 + \frac{2(1+\beta)\phi_L}{\phi_F}, 2+\beta\}$; 0 when $\lambda = 1 + \frac{2(1+\beta)\phi_L}{\phi_F}$; - when $\max\{1 + \frac{2(1+\beta)\phi_L}{\phi_F}, 2+\beta\} < \lambda < 2+\beta$;	+ when $\max\{1 + \frac{2(1+\beta)\phi_L}{\phi_F}, 2+\beta\} < \lambda < 2+\beta$ or $\lambda \leq 1$; 0 when $\lambda = 1 + \frac{2(1+\beta)\phi_L}{\phi_F}$; - when $1 < \lambda < \min\{1 + \frac{2(1+\beta)\phi_L}{\phi_F}, 2+\beta\}$	+ when $\lambda < 1$; 0 when $\lambda = 1$; - when $\lambda > 1$;

Finding in Proposition 5.7 can be generated based on Table II-5.

(Q.E.D.)

Proof of Proposition 5.8: Substituting the optimal advertising levels and prices into the objective functions under different cases, we can obtain the corresponding optimal profits. We provide the comparisons of profits among different cases as follows.

(i) Under the PM scenario, comparing the two polarized tactics, it is straightforward to obtain the profit difference between them to be the following

$$\Delta \Pi^{C-f} = \Pi^{C-TL}(\xi_L^{C-TL*}) - \Pi^{C-TF}(\xi_F^{C-TF*}) = \frac{(1-c)^2(2+\beta-\lambda)^2 k \left((1+\beta)^2 \phi_L^2 - (1-\lambda)^2 \phi_F^2 \right)}{2H_2H_3}. \text{ Consistent with}$$

the basic model, we can find that $\Delta \Pi^{C-f} > 0$ if and only if $\frac{\phi_L}{\phi_F} > \left| \frac{1-\lambda}{1+\beta} \right|$ and $\Delta \Pi^{C-f} \leq 0$ if and only if

$\frac{\phi_L}{\phi_F} < \left| \frac{1-\lambda}{1+\beta} \right|$. Moreover, the constraint $\frac{\phi_L}{\phi_F} > \left| \frac{1-\lambda}{1+\beta} \right|$ (resp. $\frac{\phi_L}{\phi_F} < \left| \frac{1-\lambda}{1+\beta} \right|$) can be expressed as

$$\min \left\{ 0, 1 - \frac{(1+\beta)\phi_L}{\phi_F} \right\} < \lambda < \max \left\{ 1 + \frac{(1+\beta)\phi_L}{\phi_F}, 2 + \beta \right\} \text{ (resp. } \max \left\{ 1 + \frac{(1+\beta)\phi_L}{\phi_F}, 2 + \beta \right\} < \lambda < 2 + \beta \text{)}.$$

(ii) Then, we compare two polarized tactics with the NPM scenario, respectively.

(a) Comparing the optimal profits between Tactic TL and NPM scenario, it is straightforward to obtain

$$\Pi^{C-TL}(\xi_L^{C-TL*}) - \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) = \widehat{F} - \frac{k(1-c)^2(2+\beta-\lambda)^2(1-\lambda)^2\phi_F^2}{2H_1H_2}, \text{ and we can get}$$

$\Pi^{C-TL}(\xi_L^{C-TL*}) > \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})$ if and only if

$$\widehat{F} > \widehat{F}_L^{EP} = \frac{k(1-c)^2(2+\beta-\lambda)^2(1-\lambda)^2\phi_F^2}{2H_1H_2} > 0.$$

(b) Comparing the optimal profits between TF and NPM, it is straightforward to obtain

$$\Pi^{C-TF}(\xi_L^{C-TF*}) - \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) = \widehat{F} - \frac{(1-c)^2 k(1+\beta)^2(2+\beta-\lambda)^2\phi_L^2}{2H_1H_3}, \text{ and we can get}$$

$\Pi^{C-TF}(\xi_L^{C-TF*}) > \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})$ if and only if

$$\widehat{F} > \widehat{F}_F^{EP} = \frac{(1-c)^2 k(1+\beta)^2(2+\beta-\lambda)^2\phi_L^2}{2H_1H_3} > 0.$$

In summary, only when $\widehat{F} > \max\{\widehat{F}_L^{EP}, \widehat{F}_F^{EP}\}$ is satisfied, the PM scenario will be optimal for the LFB.

(iii) Then, we compare the optimal profits between sub-cases (i.e., the NPM scenario, Tactic TL, and Tactic TF) of the customized advertising strategy and the non-customized advertising strategy one by one. Before conducting the comparison, to enhance the solving processes, we first obtain: If

$0 < \lambda < 1$, we have $k_{NC}^{EP} > k_{NPM}^{EP}$ and $k > k_{NC}^{EP}$; if $1 < \lambda < \beta + 2$, we have $k_{NC}^{EP} < k_{NPM}^{EP}$ and $k > k_{NPM}^{EP}$.

(a) Comparing the NPM scenario with the non-customized advertising strategy, we have

$$\Pi^{NC}(\xi^{NC*}) - \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) = 2\widehat{F} - \frac{(1-c)^2 k(1+\beta)(2+\beta-\lambda)^2 (-1+\lambda)\phi_L\phi_F}{H_1 H_4}. \text{ Therefore, if}$$

$0 < \lambda < 1$, we have $\Pi^{NC}(\xi^{NC*}) \geq \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})$; if $1 < \lambda < \beta + 2$, we have

$$\Pi^{NC}(\xi^{NC*}) \geq \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) \text{ when } \widehat{F} > \widehat{F}_1^{EP} = \frac{(1-c)^2 k(1+\beta)(2+\beta-\lambda)^2 (-1+\lambda)\phi_L\phi_F}{2H_1 H_4} \text{ and}$$

$$\Pi^{NC}(\xi^{NC*}) < \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) \text{ when } \widehat{F} < \widehat{F}_1^{EP} = \frac{(1-c)^2 k(1+\beta)(2+\beta-\lambda)^2 (-1+\lambda)\phi_L\phi_F}{2H_1 H_4}.$$

(b) Comparing the NPM scenario with Tactic TL, it can be derived that

$$\Pi^{NC}(\xi^{NC*}) - \Pi^{C-TL}(\xi_L^{C-TL*}) = \widehat{F} - \frac{(1-c)^2 (2+\beta-\lambda)^2 k(-1+\lambda)\phi_F(2(1+\beta)\phi_L + (1-\lambda)\phi_F)}{2H_2 H_4}.$$

Therefore, if $0 < \lambda < 1$ and $\max\{1 + \frac{2(1+\beta)\phi_L}{\phi_F}, 2+\beta\} < \lambda < 2+\beta$, we have

$$\Pi^{NC}(\xi^{NC*}) \geq \Pi^{C-TL}(\xi_L^{C-TL*}); \text{ if } 1 < \lambda < \min\{1 + \frac{2(1+\beta)\phi_L}{\phi_F}, 2+\beta\}, \text{ we have}$$

$$\Pi^{NC}(\xi^{NC*}) \geq \Pi^{C-TL}(\xi_L^{C-TL*}) \text{ when}$$

$$\widehat{F} > \widehat{F}_2^{EP} = \frac{(1-c)^2 (2+\beta-\lambda)^2 k(-1+\lambda)\phi_F(2(1+\beta)\phi_L + (1-\lambda)\phi_F)}{2H_2 H_4} \text{ and}$$

$$\Pi^{NC}(\xi^{NC*}) < \Pi^{C-TL}(\xi_L^{C-TL*}) \text{ when}$$

$$\widehat{F} < \widehat{F}_2^{EP} = \frac{(1-c)^2 (2+\beta-\lambda)^2 k(-1+\lambda)\phi_F(2(1+\beta)\phi_L + (1-\lambda)\phi_F)}{2H_2 H_4}.$$

(c) Comparing the NPM scenario with Tactic TF, it can be obtained that

$$\Pi^{NC}(\xi^{NC*}) - \Pi^{C-TF}(\xi_F^{C-TF*}) = \widehat{F} + \frac{(1-c)^2 k(1+\beta)(2+\beta-\lambda)^2 \phi_L ((1+\beta)\phi_L + 2(1-\lambda)\phi_F)}{2H_3H_4}.$$

Therefore, if $0 < \lambda < \min\{1 + \frac{(1+\beta)\phi_L}{2\phi_F}, 2+\beta\}$, we have $\Pi^{NC}(\xi^{NC*}) \geq \Pi^{C-TF}(\xi_F^{C-TF*})$; if

$\max\{1 + \frac{(1+\beta)\phi_L}{2\phi_F}, \beta+2\} < \lambda < \beta+2$, we have $\Pi^{NC}(\xi^{NC*}) \geq \Pi^{C-TF}(\xi_F^{C-TF*})$ when

$$\widehat{F} > \widehat{F}_3^{EP} = -\frac{(1-c)^2 k(1+\beta)(2+\beta-\lambda)^2 \phi_L ((1+\beta)\phi_L + 2(1-\lambda)\phi_F)}{2H_3H_4} \text{ and}$$

$\Pi^{NC}(\xi^{NC*}) < \Pi^{C-TF}(\xi_F^{C-TF*})$ when

$$\widehat{F} < \widehat{F}_3^{EP} = -\frac{(1-c)^2 k(1+\beta)(2+\beta-\lambda)^2 \phi_L ((1+\beta)\phi_L + 2(1-\lambda)\phi_F)}{2H_3H_4}.$$

Summarizing (i), (ii), and (iii), it is identified that the optimal advertising strategy depends on λ and \widehat{F} .

First, we derive the possible relationships of the thresholds of λ . Based on the parameter assumptions, it can be obtained that $1 < 1 + \frac{(1+\beta)\phi_L}{2\phi_F} < 1 + \frac{(1+\beta)\phi_L}{\phi_F} < 1 + \frac{2(1+\beta)\phi_L}{\phi_F}$ always holds in our model, which means that the optimal advertising strategy set is specified under different intervals of λ . Specifically, if $0 < \lambda < 1$, the optimal advertising strategy is NC; if $1 < \lambda < \min\{1 + \frac{(1+\beta)\phi_L}{\phi_F}, 2+\beta\}$, the optimal advertising strategy belongs to the set $\{NPM, TL, NC\}$; if $\max\{1 + \frac{(1+\beta)\phi_L}{\phi_F}, 2+\beta\} < \lambda < 2+\beta$, the optimal advertising strategy belongs to the set $\{NPM, TF, NC\}$. Therefore, whether Tactic TF is the optimal advertising strategy depends on the relationship between $1 + \frac{(1+\beta)\phi_L}{\phi_F}$ and $2+\beta$. By conducting the comparison, it can be found that (a) if $0 < \frac{\phi_L}{\phi_F} < 1$, there is $1 < 1 + \frac{(1+\beta)\phi_L}{\phi_F} < 2+\beta$ and the optimal advertising strategy belongs to the set $\{NPM, TL, TF, NC\}$; (b) if $\frac{\phi_L}{\phi_F} > 1$, there is $1 < 2+\beta < 1 + \frac{(1+\beta)\phi_L}{\phi_F}$, the optimal advertising strategy belongs to the set $\{NPM, TL, NC\}$.

Second, the optimal advertising strategy will be derived depending on \widehat{F} within different intervals of λ .

Case A: If $0 < \frac{\phi_L}{\phi_F} < 1$.

(a) If $1 < \lambda < 1 + \frac{(1+\beta)\phi_L}{\phi_F}$, the relationship among $\Pi^{NC}(\xi^{NC*})$, $\Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})$, and

$\Pi^{C-TL}(\xi_L^{C-TL*})$ depends on \widehat{F} . Under this situation, we can obtain $\widehat{F}_2^{EP} > \widehat{F}_1^{EP} > \widehat{F}_L^{EP} > 0$

when $k > k_1$. In this case, $\Pi^{NC}(\xi^{NC*}) > \max\{\Pi^{C-TL}(\xi_L^{C-TL*}), \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})\}$ for

$\widehat{F} > \widehat{F}_2^{EP}$; $\Pi^{C-TL}(\xi_L^{C-TL*}) > \max\{\Pi^{NC}(\xi^{NC*}), \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})\}$ for $\widehat{F}_L^{EP} < \widehat{F} < \widehat{F}_2^{EP}$;

for $0 < \widehat{F} < \widehat{F}_L^{EP}$, where $k_1 = \frac{(1+\beta)^3\phi_L^3 - (1+\beta)^2(\lambda-1)\phi_L^2\phi_F + 2(1+\beta)(1-\lambda)^2\phi_L\phi_F^2 - (\lambda-1)^3\phi_F^3}{2(2+\beta-\lambda+2\beta\lambda+\beta^2\lambda-\beta\lambda^2)((1+\beta)\phi_L - (\lambda-1)\phi_F)}$.

In addition, we can obtain $\Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) > \max\{\Pi^{NC}(\xi^{NC*}), \Pi^{C-TL}(\xi_L^{C-TL*})\}$

$\widehat{F}_L^{EP} > \widehat{F}_1^{EP} > \widehat{F}_2^{EP} > 0$ when $k < k_1$. In this case,

$\Pi^{NC}(\xi^{NC*}) > \max\{\Pi^{C-TL}(\xi_L^{C-TL*}), \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})\}$ for $\widehat{F} > \widehat{F}_1^{EP}$;

$\Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) > \max\{\Pi^{NC}(\xi^{NC*}), \Pi^{C-TL}(\xi_L^{C-TL*})\}$ for $\widehat{F}_1^{EP} < \widehat{F} < \widehat{F}_2^{EP}$;

$\Pi^{C-TL}(\xi_L^{C-TL*}) > \max\{\Pi^{NC}(\xi^{NC*}), \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})\}$ for $0 < \widehat{F} < \widehat{F}_2^{EP}$.

(b) If $1 + \frac{(1+\beta)\phi_L}{\phi_F} < \lambda < 2 + \beta$, we can obtain $\widehat{F}_3^{EP} > \widehat{F}_1^{EP} > \widehat{F}_F^{EP} > 0$ when $k > k_2$ and

$\widehat{F}_F^{EP} > \widehat{F}_1^{EP} > \widehat{F}_3^{EP} > 0$ when $k < k_2$, where

$k_2 = \frac{(1+\beta)^3\phi_L^3 - 2(1+\beta)^2(\lambda-1)\phi_L^2\phi_F + (1+\beta)(1-\lambda)^2\phi_L\phi_F^2 - (\lambda-1)^3\phi_F^3}{2(2+\beta-\lambda)(1+\beta\lambda)((1+\beta)\phi_L - (\lambda-1)\phi_F)}$. In the first scenario (i.e.,

$\widehat{F}_3^{EP} > \widehat{F}_1^{EP} > \widehat{F}_F^{EP} > 0$ and $k > k_2$),

$\Pi^{NC}(\xi^{NC*}) > \max\{\Pi^{C-TF}(\xi_F^{C-TF*}), \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})\}$ for $\widehat{F} > \widehat{F}_1^{EP}$;

$\Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) > \max\{\Pi^{NC}(\xi^{NC*}), \Pi^{C-TF}(\xi_F^{C-TF*})\}$ for $\widehat{F}_3^{EP} < \widehat{F} < \widehat{F}_1^{EP}$;

$\Pi^{C-TF}(\xi_F^{C-TF*}) > \max\{\Pi^{NC}(\xi^{NC*}), \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})\}$ for $0 < \widehat{F} < \widehat{F}_3^{EP}$. In the second

scenario (i.e., $\widehat{F}_3^{EP} > \widehat{F}_1^{EP} > \widehat{F}_F^{EP} > 0$ and $k < k_2$),

$\Pi^{NC}(\xi^{NC*}) > \max\{\Pi^{C-TF}(\xi_F^{C-TF*}), \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})\}$ for $\widehat{F} > \widehat{F}_3^{EP}$;

$$\Pi^{C-TF}(\xi_F^{C-TF*}) > \max\{\Pi^{NC}(\xi^{NC*}), \Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*})\} \text{ for } \widehat{F}_F^{EP} < \widehat{F} < \widehat{F}_3^{EP};$$

$$\Pi^{C-NPM}(\xi_L^{C-NPM*}, \xi_F^{C-NPM*}) > \max\{\Pi^{NC}(\xi^{NC*}), \Pi^{C-TF}(\xi_F^{C-TF*})\} \text{ for } 0 < \widehat{F} < \widehat{F}_F^{EP}.$$

Case B: If $\frac{\phi_L}{\phi_F} > 1$. In Case B, we have $1 < \lambda < 2 + \beta < 1 + \frac{(1+\beta)\phi_L}{\phi_F}$. In this case, results are the same as part (a) of Case A. (Q.E.D.)

Proof of Proposition 5.9:

Table II-6. Features of optimal advertising levels when the price is endogenous.

	NPM		PM	
			TL	TF
	ξ_L	ξ_F	ξ_L	ξ_F
Customized advertising	+	- if $\lambda > 1$; 0 if $\lambda = 1$; + otherwise.	+	- if $\lambda > 1$; 0 if $\lambda = 1$; + otherwise.
Non-customized advertising	- if $1 + \frac{(1+\beta)\phi_L}{\phi_F} < \lambda < \max\{1 + \frac{(1+\beta)\phi_L}{\phi_F}, 2+\beta\}$; 0 if $\lambda = 1 + \frac{(1+\beta)\phi_L}{\phi_F}$; + otherwise.			

According to the results shown in Table II-6, we can generate findings provided in Proposition 5.9. (Q.E.D.)

For the case with the budget constraint, the optimal advertising level(s) for the customized advertising strategy and non-customized advertising can be derived by solving equations (5.8) and (5.9), respectively. To solve the constrained maximization problem, we construct a Lagrangian function. Then, adopting KKT conditions, the optimal interior solutions and boundary solutions in which the budget constraint is (i) inactive and (ii) active can be obtained, respectively. Note that, for the case in which the budget constraint is inactive, the optimal decisions are equal to values in the basic model with specific conditions. Specifically, the condition is (i)

$$k > k_{NPM}^{BC} = \frac{(p-c)^2 \left((1+\beta)^2 \phi_L^2 + (1-\lambda)^2 \phi_F^2 \right)}{2(B-F-2\widehat{F})(1+\beta\lambda)^2} \quad (\text{can be converted to be$$

$$B > B_{NPM}^{BC} = \frac{(p-c)^2 \left((1+\beta)^2 \phi_L^2 + (1-\lambda)^2 \phi_F^2 \right)}{2k(1+\beta\lambda)^2} + F_b + 2\widehat{F} \quad) \quad \text{for the NPM scenario, (ii)}$$

$$k > k_{TL}^{BC} = \frac{(p-c)^2 (1+\beta)^2 \phi_L^2}{2(B-F_b-\widehat{F})(1+\beta\lambda)^2} \quad (B > B_{TL}^{BC} = \frac{(p-c)^2 (1+\beta)^2 \phi_L^2}{2k(1+\beta\lambda)^2} + F_b + \widehat{F}) \quad \text{for Tactic TL, (iii)}$$

$$k > k_{TF}^{BC} = \frac{(p-c)^2 (1-\lambda)^2 \phi_F^2}{2(B-F_b-\widehat{F})(1+\beta\lambda)^2} \quad (B > B_{TF}^{BC} = \frac{(p-c)^2 (1-\lambda)^2 \phi_F^2}{2k(1+\beta\lambda)^2} + F_b + \widehat{F}) \quad \text{for Tactic TF, and (iv)}$$

$$k > k_{NC}^{BC} = \frac{(p-c)^2 \left((1+\beta)\phi_L + (1-\lambda)\phi_F \right)^2}{2(B-F_b)(1+\beta\lambda)^2} \quad (B > B_{NC}^{BC} = \frac{(p-c)^2 \left((1+\beta)\phi_L + (1-\lambda)\phi_F \right)^2}{2k(1+\beta\lambda)^2} + F_b) \quad \text{for the non-}$$

customized advertising strategy.

In Table II-7, we summarize the optimal decisions when the budget constraint is binding (i.e. active).

Table II-7. Optimal decisions when the budget constraint is active.

Scenarios	Condition	ξ_L^*	ξ_F^*
NPM	$B < B_{NPM}^{BC}$	$\sqrt{2}(1+\beta)\phi_L \sqrt{\frac{B-F_b-2\mathbf{F}^\mathbf{L}}{k(1+\beta)^2\phi_L^2+k(1-\lambda)^2\phi_F^2}}$	$\sqrt{2}(1-\lambda)\phi_F \sqrt{\frac{B-F_b-2\mathbf{F}^\mathbf{L}}{k(1+\beta)^2\phi_L^2+k(1-\lambda)^2\phi_F^2}}$
TL	$B < B_{TL}^{BC}$	$\sqrt{2}\sqrt{\frac{B-F_b-\mathbf{F}^\mathbf{L}}{k}}$	/
TF	$B < B_{TF}^{BC}$	/	if $\lambda < 1$, $\sqrt{2}\sqrt{\frac{B-F_b-\mathbf{F}^\mathbf{L}}{k}}$; if $\lambda > 1$, $-\sqrt{2}\sqrt{\frac{B-F_b-\mathbf{F}^\mathbf{L}}{k}}$
NC	$B < B_{NC}^{BC}$	if $\lambda < 1 + \frac{(1+\beta)\phi_L}{\phi_F}$, $\sqrt{2}\sqrt{\frac{B-F_b}{k}}$; if $\lambda > 1 + \frac{(1+\beta)\phi_L}{\phi_F}$, $-\sqrt{2}\sqrt{\frac{B-F_b}{k}}$	

Table II-8. Features of optimal advertising levels when the budget constraint is active.

	NPM		PM	
	ξ_L	ξ_F	TL	TF
			ξ_L	ξ_F
Customized advertising	+	- if $\lambda > 1$; 0 if $\lambda = 1$; + otherwise.	+	- if $\lambda > 1$; + if $\lambda < 1$.
Non-customized advertising	- if $\lambda > 1 + \frac{(1+\beta)\phi_L}{\phi_F}$;			

	$+ \text{ if } \lambda < 1 + \frac{(1+\beta)\phi_L}{\phi_F}.$
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According to the results shown in Table II-8, we can obtain the optimal implementation of publicity.

Proof of Lemma 5.1: Solving the constructed Lagrangian function, the respective conditions of when the boundary solutions can be obtained are provided in Table II-7. (Q.E.D.)

Proof of Proposition 5.10: By substituting the optimal decisions into the profit functions, we can obtain the optimal profits under different advertising strategies. Then, using the same comparison approach as we adopted in Proposition 5.3 and Proposition 5.8, we can yield the results in Proposition 5.10. Note that, during the derivation, to ensure the budget in four cases (i.e., NPM, TL, TF, and NC) are all insufficient (i.e., the budget constraint is binding), we consider the case in which $B < \min\{B_{NPM}^{BC}, B_{TL}^{BC}, B_{TL}^{BC}, B_{TF}^{BC}\}$. The thresholds used in Proposition 5.10 are expressed as follows,

$$\begin{aligned} \widehat{F}_L^{BC} &= (B - F_b) \left/ \left(2 + \frac{(1+\beta)^2 \phi_L^2}{(1-\lambda)^2 \phi_F^2} \right) \right., & \widehat{F}_F^{BC} &= (B - F_b) \left/ \left(2 + \frac{(1-\lambda)^2 \phi_F^2}{(1+\beta)^2 \phi_L^2} \right) \right., & \widehat{F}_1^{BC} &= \frac{(B - F_b)(1+\beta)(-1+\lambda)\phi_L\phi_F}{(1+\beta)^2 \phi_L^2 + (-1+\lambda)^2 \phi_F^2}, \\ \widehat{F}_2^{BC} &= \frac{(B - F_b)(\lambda - 1)\phi_F(2(1+\beta)\phi_L + \phi_F - \lambda\phi_F)}{(1+\beta)^2 \phi_L^2}, & \text{and } \widehat{F}_3^{BC} &= -\frac{(B - F_b)(1+\beta)\phi_L(\phi_L + \beta\phi_L + 2\phi_F - 2\lambda\phi_F)}{(\lambda - 1)^2 \phi_F^2}. \end{aligned}$$

(Q.E.D.)

Proof of Proposition 5.11: Deriving the first-order condition of optimal advertising level(s) w. r. t B for four cases: the NPM scenario, Tactic TL, Tactic TF, and non-customized advertising strategy one by one under the situation when the budget is insufficient. It can be proven that:

$$\begin{aligned} \text{(i)} \quad \frac{\partial \xi_L^{C-NPM*}}{\partial B} &= \frac{(1+\beta)\phi_L}{\sqrt{2}\sqrt{(B - F_b - 2\widehat{F})k((1+\beta)^2 \phi_L^2 + (-1+\lambda)^2 \phi_F^2)}} > 0. \\ \frac{\partial \xi_F^{C-NPM*}}{\partial B} &= \frac{\phi_F - \lambda\phi_F}{\sqrt{2}\sqrt{(B - F_b - 2\widehat{F})k((1+\beta)^2 \phi_L^2 + (-1+\lambda)^2 \phi_F^2)}}, \text{ there are } \frac{\partial \xi_F^{C-NPM*}}{\partial B} > 0 \text{ when } \lambda < 1 \\ \text{and } \frac{\partial \xi_F^{C-NPM*}}{\partial B} &< 0 \text{ when } \lambda > 1. \\ \text{(ii)} \quad \frac{\partial \xi_L^{C-TL*}}{\partial B} &= \frac{1}{\sqrt{2}\sqrt{(B - F_b - \widehat{F})k}} > 0. \end{aligned}$$

(iii) If $\lambda < 1$, we can obtain $\frac{\partial \xi_F^{C-TF^*}}{\partial B} = \frac{1}{\sqrt{2}\sqrt{(B-F_b-\widehat{F})k}} > 0$; if $\lambda > 1$, we can obtain

$$\frac{\partial \xi_F^{C-TF^*}}{\partial B} = -\frac{1}{\sqrt{2}\sqrt{(B-F_b-\widehat{F})k}} < 0.$$

(iv) If $\lambda < 1 + \frac{(1+\beta)\phi_L}{\phi_F}$, it can be proven that $\frac{\partial \xi^{NC^*}}{\partial B} = \frac{1}{\sqrt{2}\sqrt{(B-F_b)k}} > 0$; if $\lambda > 1 + \frac{(1+\beta)\phi_L}{\phi_F}$, we can

$$\text{obtain } \frac{\partial \xi^{NC^*}}{\partial B} = -\frac{1}{\sqrt{2}\sqrt{(B-F_b)k}} < 0. \quad (\text{Q.E.D.})$$