SUPPLY CHAIN RESILIENCE AND SOCIAL WELFARE ENHANCEMENT UNDER COVID-19 PANDEMIC

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CERTIFICATE OF ORIGINALITY

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__________________________ (Signed)

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Abstract

The outbreak of COVID-19 has posed serious threats and challenges to supply chain management (SCM). Even though the pandemic has been announced as all over since 5 May 2023, there still exists profound influence. To cope with the challenges (such as the reshaped consumer behavior, supply disruptions, demand depression, etc.) and seek survivals, proper measures should be taken to build resilient supply chains under/after the pandemic. Under the pandemic, individuals' worries of infection would create huge troubles for the society. On one hand, due to the severe unemployment issue during the pandemic, firms should pay attention to general welfare of the people (e.g., consumer and workers' welfare) so as to achieve sustainability and bear the needed social responsibility under COVID-19. On the other hand, the government should also play an essential role in social performance. The government's decisions (e.g., vaccine ordering strategy, subsidy design, etc.) will directly affect the people's benefit and supply chain's performance. After the pandemic, the reshaped consumer behavior constantly affects the firm's operations and requires the firm to adapt the new normal. Overall, it requires the companies' and the government's joint efforts to establish a resilient supply chain and enhance the social welfare to cope with the pandemic.

Motivated by various observed critical challenges brought by COVID-19 on SCM and social performance, this thesis is conducted to explore the potential solutions that can help supply chains achieve resilience and enhance the social welfare under/after the pandemic. We would like to provide guidance on both business decisions (e.g., pricing, product quality, employment level, service level, etc.) for companies and mechanism designs (e.g., subsidy program, vaccine ordering policy) for governments, aiming to help supply chains and people better survive the pandemic and have a long-term development after the pandemic. To capture the features of COVID-19 and its impacts on supply chain operations, we adopt the practice-based analytical modeling approach in this thesis. First, a systematic literature review is conducted to examine the impacts and specific challenges brought by the pandemic to supply chain operations. We analyze the current research status and propose a comprehensive research framework with a solid future research agenda.

Then, based on the research gaps identified in the first step, analytical models are constructed to investigate the operations management issues from three perspectives: (i) *service operations*: the value of WhatsApp shopping service operations (WSO) in helping the company to survive the pandemic and

enhancing social welfare; (ii) *production*: the government's role and the impacts of government's subsidy on mask production and social welfare; and (iii) *procurement*: the government's optimal vaccine ordering strategy that maximizes the total social welfare. For service operations, the results indicate that WSO is not always effective to combat COVID-19. In particular, we uncover that when the consumers' fear of infection is polarized (i.e., extremely low or high), WSO could be never recommendable. For mask production, we find that without the government's price control (i.e., the manufacturer decides the mask price), the manufacturer and consumer subsidy programs are equally efficient in enhancing consumer surplus and reducing harms on social health risk. For vaccine ordering, the findings suggest the government need not order vaccines as early as possible, and the government should select its vaccine supplier based on the disease's infection rate in the society in a dynamic manner.

To conclude, motivated by the potential challenges caused by the COVID-19 pandemic on SCM and social welfare, this thesis conducts a series of analytical studies to derive scientifically solid insights. These insights provide pertinent managerial implications to both supply chains and governments to improve their decision making. This thesis contributes to the development of SCM during the unexpected pandemics (e.g., COVID-19) from both the academic and practical perspectives. It helps supply chains better survive the pandemic and achieve sustainable development after the pandemic.

Publications Arising from this Thesis

Journal Publications and Working Papers

[1] **Xu, X.**, Sethi, S.P., Chung, S.H., Choi, T.M. (2023). Reforming global supply chain management under pandemics: The GREAT-3Rs framework. *Production and Operations Management*, 32, 524–546. (Related to Chapter 2)

[2] **Xu, X.**, Sethi, S.P., Chung, S.H., Choi, T.M. (2023). Ordering COVID-19 vaccines for social welfare under information updating: Optimal order policy and supplier selection in the digital age. *IISE Transactions*, forthcoming. (Related to Chapter 5)

[3] **Xu, X.**, Choi, T.M., Chung, S.H., Guo, S. (2023). Collaborative-commerce in supply chains: A review and classification of analytical models. *International Journal of Production Economics*, forthcoming. (Related to Chapter 2)

[4] **Xu, X.**, Choi, T.M., Chung, S.H., Shen, B. (2022). Government subsidies and policies for mask production under COVID-19: Is it wise to control less? *IEEE Transactions on Engineering Management*, published online: 10.1109/TEM.2022.3198101. (Related to Chapter 4)

[5] **Xu, X.**, Chung, S.H., Lo, C.K., Yeung, A.C. (2022). Sustainable supply chain management with NGOs, NPOs, and charity organizations: A systematic review and research agenda. *Transportation Research Part E: Logistics and Transportation Review*, 164, 102822. (Related to Chapter 4)

[6] **Xu, X.**, Siqin, T., Chung, S.H., Choi, T.M. (2021). Seeking survivals under COVID-19: The WhatsApp platform's shopping service operations. *Decision Sciences*, published online: 10.1111/deci.12552. (Related to Chapter 3)

Conferences

[1] **Xu, X** (presenter) (with Choi, T.M., Chung, S.H., Shen, B). Government subsidies and policies for mask production under COVID-19: The use of blockchain. *The Operations and Supply Chain Management Conference*, Chatham Street, Liverpool, 27-29, June 2023.

[2] **Xu, X** (presenter) (with Sethi, S.P., Chung, S.H., Choi, T.M). Ordering COVID-19 vaccines for social welfare under information updating: Optimal dynamic order policies and vaccine selection. *The POMS International Conference*, Budapest, Hungary, 29 June-1 July 2022.

[3] **Xu, X** (presenter) (with Sethi, S.P., Chung, S.H., Choi, T.M). Reforming global supply chain operations management under pandemics: The GREAT-3Rs framework and research agenda. *The INFORMS Annual Conference 2021*, Anaheim, CA, USA, 24-27, October 2021.

[4] **Xu, X** (presenter) (with Choi, T.M., Chung, S.H., Shen, B). Government subsidies for mask production under COVID-19: Cheating prevention and price control. *The MSOM Conference 2021*, Indiana, USA, 7-10, June 2021.

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My PhD journey started at a very speical time point — the beginning of the COVID-19 pandemic, and coincidentally, it terminated after the end of the pandemic. Just as mentioned in this thesis, COVID-19 has brought a series of challenges to all aspects of our lives, and there is no exception for my research life. While luckily, I have received greatest support and kindest help from various parties in these three years, without which I may not able to complete this thesis so smoothly. Therefore, I would like to express my sincere gratitudes to them here.

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Chapter 1 Introduction

1.1 Background and Motivation

Year 2020 is an extraordinary year in which we have witnessed great changes in the whole world due to the unexpected COVID-19 outbreak. Since the World Health Organization (WHO) formally announced that the COVID-19 is a global pandemic in early 2020, all walks of life, as well as all business operations, have been affected significantly. It is reported that the COVID-19 pandemic has led to a deterioration of business performances of almost all enterprises and resulted in the rapid growth of bankruptcy figures in many countries. From January 2020 to August 2020, the annual number of bankruptcies of large international corporations has increased nearly 200% during COVID-19 (Wang et al. 2020a). Nowadays, despite the pandemic has been announced as all over since 5 May 2023[1], companies still face a series of post-pandemic challenges including continuity of supply and production issues (Anderson et al. 2023). Indeed, disruptions in both the demand and supply sides created by COVID-19 are the source of the problem (Jiang et al. 2023), and they also uncover the fragile and inefficient nature of supply chain management (SCM). Cohen et al. (2018)'s industrial survey reveals that many global firms are restructuring their supply chains while the tradeoffs of multiple factors (e.g., markets, suppliers, and technologies) along with risk factors are highly complex. To cope with the severe challenges (e.g., demand depression, supply disruption, etc.) caused by the unexpected pandemics such as COVID-19, supply chain resilience should be paid great attention to. Here, supply chain resilience refers to the ability to survive, adapt and grow when being confronted with turbulent change, e.g., supply chain disruptions (Pettit et al. 2013). By achieving supply chain resilience, companies can recover the procurement of material and keep the information and cash flow during the pandemic (Gu et al. 2021, Xu et al. 2023b, Ivanov and Keskin 2023).

Social related problems are another critical issue created by COVID-19, which are associated with social responsibility. According to Lee and Tang (2017), the external stakeholders of a supply chain (e.g., workers, consumers, and governments) are the key aspects in social responsibility issues (Huang et al. 2022). For example, unemployment problem got increasingly worse during COVID-19. It is

[1] See WHO official website: https://www.who.int/europe/emergencies/situations/covid-19.

reported that the US unemployment rate had risen sharply from 3.8% in February 2020 to around 15% in May 2020 (Kochhar 2020). Meanwhile, individual’s worry of infection also creates big troubles for companies and governments (Choi and Shi 2022). The infection probability of the disease will directly influence the consumers’ willing to go to the physical store as well as their welfare. Under this circumstance, the whole society and government are desperate for firms to take more social responsibilities and focus on the issue of social welfare. Consequently, seeking a way to maintain the employment level and offset consumer’s concerns about COVID-19 is the biggest challenge faced by firms with social welfare in mind (Choi, 2021b). Specifically, firms should pay attention to general welfare of the people (e.g., consumer and workers’ welfare) so as to achieve sustainability and bear the needed social responsibility under the COVID-19 pandemic (Lee, 2021). It requires firms to have a deep understanding of the impacts of COVID-19 not only on the firm’s operations decisions (e.g., pricing, production, employment level) and profit, but also on the total social welfare including consumer welfare and workers’ welfare (Feng et al., 2022).

On the other hand, the government should also play an essential role in social performance. The government’s operations decisions (e.g., vaccine ordering strategy, subsidy design, countries’ alignment, etc.) will directly affect the consumer’s behavior and supply chain’s performance under the pandemic. Generally, a well-designed subsidy program is commonly implemented by the government to help firms survive the pandemic (Choi 2020, Liu et al. 2021) and enhance the consumer affordability of the product (Arifoğlu and Tang, 2022), which can eventually benefit the total social welfare. In real practice, after the outbreak of COVID-19, the European Union has provided funding for a broad range of projects; Japan’s Ministry of Economy, Trade and Industry has conducted a subsidy project to support mask manufacturers and individual businesses operators affected by COVID-19. Most recently, the White House announced an American rescue plan in January 2021, in which US$1.9 trillion will be provided to help its citizens to survive COVID-19. Hence, it requires the companies’ and the government’s joint efforts to establish a resilient supply chain and enhance the social welfare under the pandemic.

1.2 Research Objectives

Motivated by the critical challenges brought by COVID-19 on the SCM and social performance, this doctoral thesis is conducted to explore the potential solutions that can help the supply chain to achieve resilience as well as enhance the social welfare under the pandemic. We would like to provide guidance on both business decisions (including pricing, product quality, employment level, and service level) for the company and mechanism design (including subsidy program and vaccine ordering policy) for the government, aiming to help the companies better survive the pandemic and have a long-term development after the pandemic. Specifically, this doctoral thesis would reach the following main objectives from three different aspects: (i) service operations, (ii) production, and (iii) procurement:

(i) For the service operations issue, this work explores the value of re-establishing the channel strategies (e.g., adopting the WhatsApp shopping service operations) in helping the company to survive the pandemic and enhancing social welfare. Particularly, we include both the consumer and workers' welfare in analyses.

(ii) For the production issue, this work investigates the government's role in mask production and examines the impacts of different government's subsidy schemes (i.e., manufacturer subsidy and consumer subsidy) on the mask supply chain performance and social welfare.

(iii) For the procurement issue, this work figures out the government's optimal COVID-19 vaccine ordering strategy and supplier selection strategy that maximizes the total social welfare in a competing scenario. We particularly evaluate the influences of critical factors including the infection rate and vaccine efficacy levels.

1.3 Research Methodology

To capture the features of COVID-19 and its impacts on supply chain operations, we mainly use the practice-based analytical modeling approach in this doctoral thesis. First, we conduct a systematic literature review to examine the impacts and specific challenges brought by the pandemic to supply chain operations. Second, based on the research gaps identified in the first step, we employ a multi-methodological approach (i.e., combining analytical models with in-depth semi-structured interviews) to investigate the impacts of COVID-19 on the supply chain and the government's decisions. We finally generate useful managerial implications for supply chain resilience and social welfare enhancement under/after the pandemic. We introduce the methodology used in each Chapter as below.

(i) In Chapter 3, we first conduct interviews with salespeople and then build a standard consumer utility-based model based on the interview findings. Our model captures the consumer's change of behavior under/after the pandemic, and innovatively includes workers' welfare into the total social welfare. By doing comparisons among different scenarios, we analytically examine the value adopting the WhatsApp shopping service operations in helping the company to survive the pandemic and enhancing social welfare.

(ii) In Chapter 4, we also conduct an interview with a mask company's CEO and establish consumer utility-based stylized models to examine government's subsidies and policies in the mask supply chain. We particularly consider the social health risk in the social welfare during the COVID-19 outbreak. Our analytical and numerical findings contribute to healthcare operations management and generate managerial insights for mask supply chain management under/after COVID-19 with industrial validation.

(iii) In Chapter 5, we combine the consumer utility-based model into a newsvendor model, which captures the stochastic demand of vaccination under the pandemic. Particularly, we consider a two-stage two-ordering inventory model with Bayesian information updating. Using dynamic programming, we derive the government's optimal vaccine ordering policy that maximizes the total social welfare during the COVID-19 pandemic.

1.4 Research Significance and Contribution Statement

This study contributes to the development of SCM during the unexpected pandemics (e.g., COVID-19) from both the academic and practical perspectives. We analytically examine the measures of supply chain resilience and social welfare enhancement from three aspects: service operations, production, and procurement. The major contributions include:

First, this work proposes an innovative research framework for SCM under the pandemic based on a systematic literature view. Five future research agenda are raised to fill the existing research gaps.

Second, the value of WhatsApp shopping service operations (WSO) adoption under the pandemic is evaluated. To our best knowledge, this study is the first one in the operations management (OM) and decision sciences literature, which investigate WSO under COVID-19. We analytically verify the significance of adopting WSO to dampen the negative impacts brought by COVID-19 on retail operations (e.g., eliminating the demand reduction in physical stores, increasing total profits, etc.) as well as establish a resilient supply chain under the pandemic. Scientific guidance for firms and policy makers on the implementation of this new model is provided. In addition, we take the special consideration of workers' welfare when evaluating the welfare performance in our research, which is crucial under COVID-19 while is still under-explored in the OM literature.

Third, this is the first study to analytically evaluate the efficiency of government subsidy programs in the mask supply chain under a disease outbreak such as COVID-19. We highlight the impacts of government's subsidies on eliminating the supply disruption and enhancing social welfare. The insights derived not only contribute to the OM literature by enriching the studies on government subsidies but also generate managerial insights for governments, manufacturers, and consumers regarding the proper use of subsidy programs to achieve supply chain resilience and social welfare enhancement during the COVID-19 outbreak.

Finally, based on the real-world observations, this study investigates the government's dynamic vaccine ordering strategy (including the optimal ordering quantity, ordering point, supplier selection decisions) with the consideration of information updating. The analytical findings can provide guidance for the government's COVID-19 vaccination program to maximize the social welfare.

1.5 Thesis Outline

This thesis is organized as follows. First, Chapter 2 reviews the existent literature and examines industrial practices of supply chain operations under the pandemic. Then, Chapter 3 explores the value of WhatsApp shopping service operations in helping the company to survive the pandemic and enhancing social welfare. Chapter 4 examines the impacts of government's subsidy scheme on the mask supply chain performance and social welfare under the pandemic. Chapter 5 figures out the government's optimal vaccine ordering strategy that maximizes the total social welfare under the pandemic. Finally, Chapter 6 summarizes the major findings with managerial insights and discusses future research directions. Besides, supplementary materials (including figures and tables) are available in Appendix A and all the mathematical proofs for Chapters 3, 4, and 5 are in Appendix B. Note that, the notations and mathematical models in Chapters 3 to 5 are self-contained and only valid for each chapter. The following Figure 1-1 presents the outline of this thesis with methodologies.

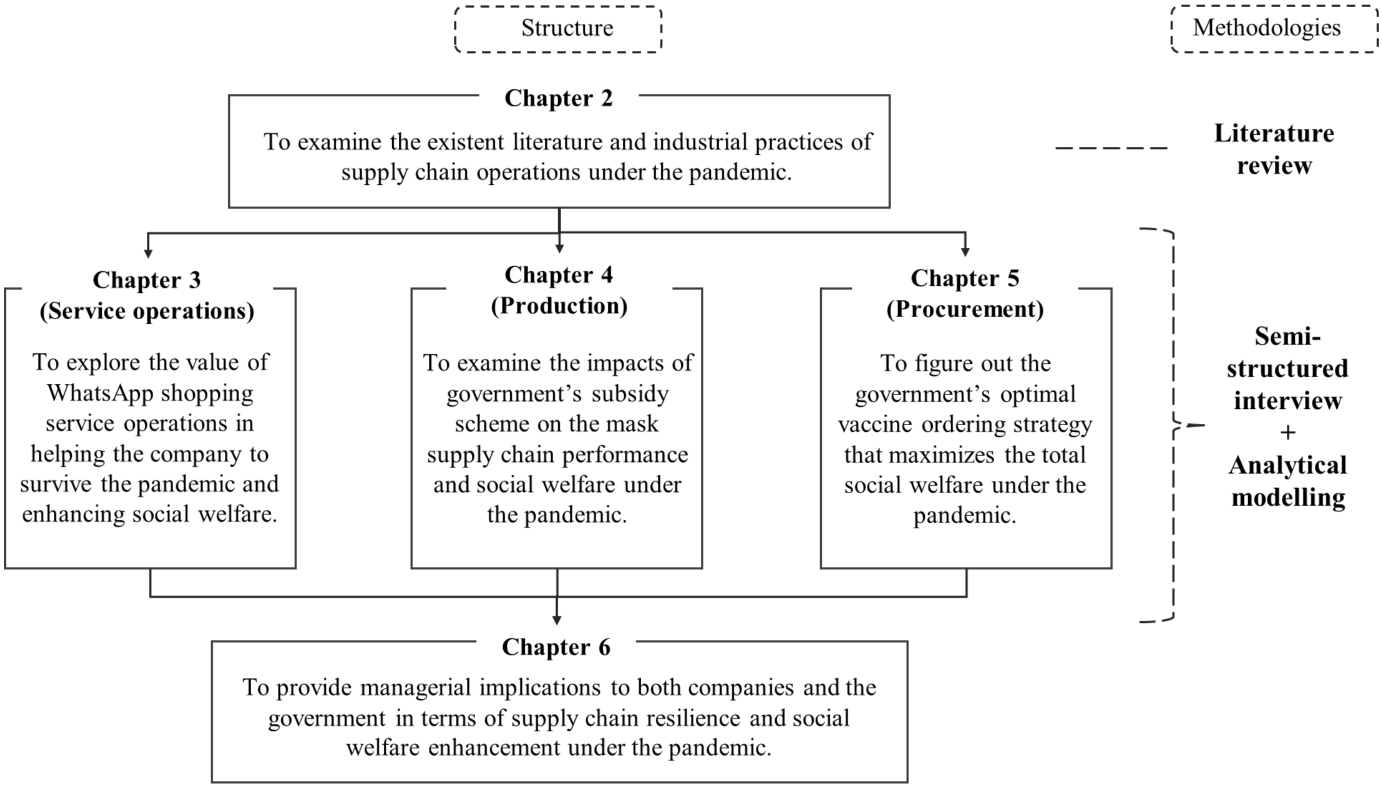

Figure 1-1. Outline of the thesis.

Chapter 2 Literature Review[2]

A recent Harvard Business Review article (Carlsson-Szlezak et al. 2020) articulated that the COVID-19 pandemic will affect the global economy from both the demand and supply sides. On the demand side, the pandemic brings shocks to financial markets as well as reduces consumer confidence. On the supply side, it leads to the closure of production, handicapped logistics, and shortages of critical components. Similar views are reported by Forbes (Tang and Yang 2020) and California Management Review (Li and Nell 2020). We hence follow their classification to conduct the literature review based on demand and supply sides risks.

2.1 Demand Side Risk under Pandemic

2.1.1 Demand disruption

Demand disruption usually refers to the sudden demand variability or radical change of customer fragmentation (Ivanov et al. 2019, Xu et al. 2023a). It is crystal clear that demand disruption is very likely to happen under an epidemic pandemic such as COVID-19 and may create a ripple effect (Ivanov and Dolgui 2020a). Recently, two papers focus on examining the demand disruption risk under the pandemic. First, Ivanov and Das (2020) conduct simulation studies to explore the ripple effect of an epidemic outbreak in global supply chains. Three distinctive scenarios are modeled and the authors put a strong emphasis on investigating the uncertainty of market disruption with different durations. The authors interestingly show that the combinatorial effects of market disruption and other negative events may indeed benefit the supply chain. Second, Cheema-Fox et al. (2021) use data from over three thousand global companies in different industries to empirically study the firms' resilience and responsive operations under a sharp market decline during COVID-19. The authors uncover that the company with "positive sentiment" tends to possess stronger resilience and response-ability. As we can see, both Ivanov and Das (2020) and Cheema-Fox et al. (2021) reveal that demand disruption under the pandemic is an issue that can be addressed if proper measures are imposed.

To generate more useful insights for SCM to combat demand disruption, we further search and

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[2] A part of this chapter has been published in "Xu, X., Sethi, S.P., Chung, S.H., Choi, T.M. (2023). Reforming global supply chain management under pandemics: The GREAT-3Rs framework. *Production and Operations Management*, 32, 524–546." and "Xu, X., Choi, T.M., Chung, S.H., Guo, S. (2023). Collaborative-commerce in supply chains: A review and classification of analytical models. *International Journal of Production Economics*, forthcoming."

review some important OM literature related to demand disruption risks. For example, Chen and Xiao (2009) and Zhang et al. (2012) build analytical models to examine the impacts of demand disruptions on supply chain coordination. Specifically, Chen and Xiao (2009) propose two coordination schedules, namely, the “linear quantity discount schedule” and “Groves wholesale price schedule”. They prove that both schedules have their superiorities to fight against demand disruption under certain conditions. Zhang et al. (2012) find that the supply chain members must adjust the original revenue-sharing contracts when there exist demand disruptions; otherwise, the supply chain performance will be harmed. Moreover, Xu et al. (2018a) construct an “online-to-offline” (O2O) supply chain model with online subsidies, through which they analyze the value of online subsidies in terms of eliminating the demand disruptions. To summarize, we conclude that the demand disruption risks under pandemic are present while luckily, they may not be that fatal. Some measures, such as proper coordination schedules and subsidy programs may be helpful.

2.1.2 Demand uncertainty

Global markets are affected by COVID-19 and pandemics naturally would magnify market demand uncertainty and vulnerability. In particular, companies are placing much bigger orders to compensate for the probable delays and shortages in supplies. The bullwhip effect (Lee et al. 1997) is hence magnified under COVID-19 and this was recently reported by Wall Street Journal[3]. This situation was even more severe when many factories went downsizing over the past decades. Prior literature related to demand uncertainty mainly works on solving inventory management problems. For example, realizing the challenges of demand uncertainty in humanitarian operations, Rottkemper et al. (2011) develop an optimization model based on penalty costs for non-satisfied demand to balance inventories and to reduce total non-served demand. Wang et al. (2009) and Liu and Zhao (2012) investigate how demand uncertainty affects emergency resource usages and planning in epidemic areas. To figure out optimal material distribution decisions under pandemic, Wang et al. (2009) develop a multi-objective stochastic optimization model with “time-varying demand”. The authors incorporate epidemic diffusion into the model. Then, Liu and Zhao (2012) construct and solve an integrated and dynamic optimization model with time-varying demand. They provide useful guidelines for decision-makers to solve the emergency rescue problem with uncertain demand. Van der Laan et al. (2016)

[3] URL: https://heizerrenderom.wordpress.com/2021/02/23/om-in-the-news-covid-19-and-the-bullwhip-effect/.

realize the high demand uncertainty nature of medical aid items under epidemics. The authors empirically study the demand prediction and order planning problem for medical items. Parvin et al. (2018) examine the optimal allocation of malaria medications in a three-layer centralized health supply chain system, in which the market demand uncertainty is modeled by a two-stage stochastic programming approach. Shamsi et al. (2018) develop a specific "options contract" for vaccine procurement under demand uncertainty. The authors build an analytical epidemic model to capture the establishment and spread of an infectious disease. They also apply the log-normal distribution to model the uncertain demand. The authors argue that different from the commonly used normal distribution, the log-normal distribution can well-capture the skewed probability distribution, which is known to be common for demand under a pandemic (e.g., with a long right tail). To cope with demand uncertainties under epidemic, governments should consider the social cost associated with the infected individuals and the specific data when making the optimal decisions. Li et al. (2021) and Shen and Sun (2023) notice the huge uncertainty of demand under the COVID-19 pandemic and make efforts on supply chain resilience. To be specific, Li et al. (2021) analyze the potential influence of COVID-19 on passenger air transport demand and make forecase under different cases by using simulation method. Their results reveal that the two forces (i.e., supply restriction, demand depression) will have opposite impacts on air transport demand with respect to different passenger segments. Shen and Sun (2023) use quantitative operational data from JD.com to evaluate the challenges brought by COVID-19 (e.g., exceptional demand) and corresponding measures in Chinese market. The authors conclude that it is necessary and effective for firms, the government, and the whole society to make joint efforts to control the market demand under the pandemic.

2.1.3 Consumer/Social behaviors

COVID-19 changes our daily life. Although the pandemic may be temporary, changes in consumer/social behaviors in supply chains are likely long-lasting (Downes 2020). For instance, consumers are more willing to have online shopping while less likely to take public transports. Thus, it is natural to consider consumer/social behaviors when exploring the impacts brought by pandemics like COVID-19. To help both governments and individuals develop better control policies for fighting an influenza pandemic, Larson (2007) establishes a "nonhomogeneous probabilistic mixing" model to examine how an individual's heterogeneity and social behaviors could affect the evolution of the disease. Singh et al. (2020) conduct a simulation analysis of the public distribution systems network to explore the impacts of COVID-19 on food supply chains. The authors consider the consumers' flexibility in ordering items, which is an important modeling feature. Choi (2020) analytically examines the values of "bring-service-near-your-home" operations for small service providers to survive COVID-19. In his model setting, consumers make their decisions not only based on the service fee but also factors such as the hygiene level and average distance to the firm. The author also explores the roles played by the government under the pandemic. Muggy and Stamm (2020) work on the decentralized beneficiary's "last mile behavior" in humanitarian supply chains. The authors build a game-theoretic model to measure the impact of uncoordinated decisions on supply chain performance. Their findings guide how to change decentralized decisions so that they will approach the ones under the coordinated system. Observing that consumers tend to shift from offline stores to online, Hwang et al. (2021) pay attention to examining the retailer's omnichannel operations under COVID-19. The authors empirically examine the implications of the COVID-19 pandemic and government interventions on an omnichannel retailer's performance. They offer helpful omnichannel operations suggestions for retailers to adapt to the pandemic under the new normal. Observing the firm's closure decisions under COVID-19, De Vaan et al. (2021) study how the social learning impacts the firm's operations decisions. The authors claim that not only the consumer's behavior but also the competitors' behavior can provide signals for the firm's closure decisions. Liu et al. (2021) conduct an empirical study to analyze the effect of providing coupon on consumer spending in Chinese market. The authors verify the effectiveness of the coupon program on stimulating consumption under COVID-19, and also highlight the importance of taking behavioral factors into consideration when designing the program. From the above studies, we notice that consumer/social behaviors would shift and influence SCM. This deserves the companies' attention.

2.2 Supply Side Risk under Pandemic

2.2.1 Supply disruption

Supply-side uncertainty is an inherent part of SCM (Li et al. 2017) and supply disruptions are very critical (Shan et al. 2022). Usually, firms cannot recover rapidly from disruptions (Hendricks and Singhal 2005). Before the occurrence of COVID-19, Cohen et al. (2018) discuss the offshore production and reshoring decisions in global supply chains. With industrial inputs and data analyses, the authors uncover a few insights and establish a few hypotheses, e.g., "Restructuring of global supply chains is taking place in all industries and geographies (P.S.: Hypothesis 1 of Cohen et al. (2018))", "China and Eastern Europe have emerged as the dominating destinations for offshoring (P.S.: Hypothesis 2)" and "Natural hedging occurs in many industries (P.S.: Hypothesis 4)". Global companies have long considered supply disruption risk in planning the optimal supply chain configuration. COVID-19 probably pushes the situation further and companies need to think even more thoroughly and consider the option of reshoring even more urgently than ever.

Supply disruption risk is the most popular and urgent issue that needs to be resolved under COVID-19 for SCM. This kind of risk is inevitable for supply chains due to the lockdowns of cities during the pandemic. Numerous studies investigated this topic and provided useful guidelines for SCM about how to combat the negative effects brought by supply disruptions. In the literature, different research methodologies are adopted for exploring supply disruption and these include (i) case studies and empirical studies, (ii) game theory, and (iii) computation-based optimization problems.

First, for case studies and empirical studies, Govindan et al. (2020) develop a practical decision supporting tool to help reduce supply disruption risks in the healthcare supply chain system. The authors further conduct case studies to evaluate the performance of their proposed system and show promising results. Handfield et al. (2020) focus on exploring trade disruptions (e.g., Brexit and the USA imposing tariffs) for SCM under the recent COVID-19 pandemic. Through two case studies, the authors explore the impacts brought by trade disruption risk on the supplies and the proper design of future global supply chains. The authors expect to witness a dramatic transformation of global supply chains rather than imposing tariffs in the new normal. Then, in the context of quantitative empirical research, Nikolopoulos et al. (2021) highlight the significant disruptions in both up- and down-streams of supply chains. The authors use data collected from different countries (including the USA, India, UK, etc.) up to mid-April 2020 to provide short-term predictions on the COVID-19 pandemic and its effect on SCM. They argue that the findings are very useful for enterprises and policy-makers. Similarly, Shen and Sun (2021) collect the data of JD.com and emphasize the critical supply disruption problem facing by the Chinese market. By analyzing the practical measures taken by JD.com under COVID-19, the authors summarize that the operational flexibility and collaboration among supply chains should be effective ways to help the firm to cope with the severe supply disruptions under the pandemic. Chundakkadan et al. (2022) evaluate the role of government support to small and medium enterprises. By empirically analyzing the firm-level data from over a dozen countries, the authors conclude that those firms with financial constraints tend to shut down their operations due to supply disruptions, and most of them are supported by the government. Cui et al. (2022) interestingly examine the operations problem with social issues, that is, how the disruption problem caused by city lockdowns influences the related gender equity in terms of research productivity. Their empirical findings verify the existence of fairness issue in productivity due to the disruption problem.

Second, for analytical studies, game theory is frequently adopted to explore the supply disruption risk under pandemics. Chick et al. (2008) develop an integrated analytical model with considerations of both the government's and manufacturer's decisions in a supply chain for vaccines. They reveal that the supply disruption of vaccines will be caused by a lack of coordination. Chen (2013) uses game-theoretical models to derive the optimal procurement design under supply disruptions (caused by disease outbreaks) and heterogeneous beliefs between buyers and suppliers. The authors show that heterogeneous beliefs of disruption probability will result in severe production inefficiencies, which should be avoided as much as possible. Ivanov (2022) proposes an analytical "viable supply chain" model using the dynamic systems theory and dynamics optimal control. The author verifies the supply chain's performance in terms of recovering and re-building of the supply chain capability after the COVID-19 pandemic. Ivanov and Dolgui (2020b) use the "dynamic game-theoretic modeling" approach to investigate the viability of "intertwined supply networks". They focus on uncovering the impacts brought by disruptions and the critical "ripple effect". The authors evaluate how the existence of backup suppliers and "subcontracting facilities" affect SCM under supply disruption risks.

Finally, there are a substantial number of papers that explore supply disruptions under pandemic by using computation-based approaches, including simulation, optimization, etc. First of all, some inventory control problems are examined. For instance, based on simulation-based analysis, Rottkemper et al. (2011) work on the optimal inventory relocation problem for humanitarian operations. The authors surprisingly find that considering future disruptions can sometimes be helpful to balance inventories and reduce the total "non-served" demand. Ekici et al. (2014) construct simulation models to study the optimal food distribution problem during an influenza pandemic with the consideration of supply chain disruptions. Their experimental results indicate that the capacity bottleneck, as well as the level of supply disruptions, will be reduced significantly by implementing the “voluntary quarantine” mechanism. Shamsi et al. (2018) analytically develop a specific option contract for vaccine procurement by adopting the bi-level optimization approach with a nonlinear optimization problem. In their model, two suppliers, called the “main and back-up” suppliers, are explored in the presence of supply disruption. The authors conclude that vaccine reservations could be an effective way to deal with those infectious disease epidemics and help achieve “post-pandemic resilience” for the supply chain. By building and solving a “dynamic hybrid facility network” model, Mishra and Singh (2022) find that capacity expansion could be an effective approach to address the problem of supply disruption in a supply chain. The authors adopt both “mixed-integer nonlinear programming” and “linear programming” approaches in their modeling analyses.

Also, several computation-based studies in the literature are devoted to providing risk mitigation measures for supply chains to survive pandemics. For instance, Paul and Venkateswaran (2020) adopt the “Exploratory Modelling and Analysis” methodology to discuss robust supply chain optimal policies for mitigating an epidemic. The authors construct simulation models and run computational experiments to examine the role of drug supply disruptions in controlling the epidemic dynamics. To minimize the negative influence of disruptions under the COVID-19 pandemic, Paul and Chowdhury (2021) propose a nonlinear programming recovery optimization model for assisting decision-making in revising the optimal production plan. Their study highlights the superiority of a proper combination of two recovery strategies, namely (i) lifting production capacity, and (ii) implementing emergency sourcing with supplier collaboration.

Moreover, numerous studies (i) reveal the importance of building a resilient supply chain system and (ii) propose various practical strategies, under epidemic pandemics. To be specific, Dasaklis et al. (2017) develop a linear programming model to study emergency supply chain operations. The results show that supply disruptions in vaccine supply chains appear at the “middle stage” of the major supply period. The authors hence highlight the necessity of establishing an emergency supply chain model to deal with a pandemic outbreak. Ivanov (2020) and Ivanov and Das (2020) conduct simulation-based analyses to examine how to strengthen the resilience of supply chains when facing disruptions that are triggered by epidemic outbreaks like COVID-19. In particular, Ivanov (2020) predicts the impacts of epidemic outbreaks on SCM along with proposals of managerial actions. They surprisingly show that disruptions, especially short-term disruptions, may positively affect the supply chain performance during an epidemic outbreak under some conditions. Ivanov and Das (2020) analytically model the ripple effect brought by an epidemic outbreak on SCM. The authors build optimization models to determine the (potential) recovery paths for supply chains under pandemics. Their simulation results interestingly show that the combined effects of disruption uncertainty and other negative events may indeed benefit the supply chain in some cases. Singh et al. (2020) propose a simulation model for studying logistics systems in food supply chains under COVID-19. In their model, supply disruptions are considered. The authors aim at establishing a tool to achieve a resilient food supply chain system.

2.2.2 Resource allocation

Resource allocation problem (from the supply side) is the hottest issue being discussed in the related literature in the presence of pandemics. Among all the emergency resources, healthcare resources should undoubtedly be the most crucial ones. A multitude of works has explored the optimization problems associated with allocation strategies for healthcare resources based on computation-based approaches. For instance, Wang et al. (2009) build a multi-objective stochastic programming model to study the optimal medical material distribution problem. The authors incorporate the epidemic diffusion rule as well as the delay brought by the disease epidemic into the model construction. Savachkin and Uribe (2012) establish a simulation optimization model to determine the optimal dynamic allocation strategies for limited healthcare resources such as vaccines. The authors aim at finding the optimal solution which balances both the ongoing and potential impacts under an influenza pandemic. Their computational results show that when the resource availability cannot meet the basic requirement, it is valuable to increase the additional resource availability. Rachaniotis et al. (2012) propose a simulation model to study the optimization problem of scheduling a single available resource in a pandemic area. The authors use a real case of the influenza epidemic in Greece to validate the model and demonstrate the good performance of their proposal. Ekici et al. (2014) combine the “disease spread” model with an optimal resource allocation model to estimate the demand for food under a pandemic. The authors derive the optimal food allocation strategy. Liu and Zhang (2016) establish a dynamic logistics model for medical resource allocation considering time-varying demand and forecasting mechanisms. The authors build and solve a 0-1 programming problem to find the first best medical resource allocation. Dasaklis et al. (2017) consider the “dynamic spread” of a pandemic outbreak. They find the optimal resource allocation decisions via solving the corresponding linear programming model. Long et al. (2018) and Büyüktahtakın et al. (2018) conduct research concerning Ebola outbreaks. To be specific, Long et al. (2018) develop a two-stage model for an optimal spatial allocation problem with limited intervention resources under the Ebola pandemic. The authors conduct a comparison study among four approaches, namely the heuristics approach, a greedy policy, a myopic policy, and an "approximate dynamic programming" algorithm. Their results surprisingly uncover that the myopic policy can be the best method to resolve this optimal allocation problem. Parvin et al. (2018) design efficient medicine allocation schemes for malaria medication. The authors explore the problem in the context of resource-constrained countries. They also examine from both the strategic and tactical levels. Through case analyses and numerical studies, the authors validate the performance of their proposed model in terms of medicine allocation. Büyüktahtakın et al. (2018) develop a novel "epidemics–logistics mixed-integer programming" model to examine how to optimally allocate resources for controlling the Ebola outbreak. Then, by changing the capacity constraint in the model proposed by Büyüktahtakın et al. (2018), Liu et al. (2020) extend the "epidemics–logistics mixed-integer model" and apply it for controlling the H1N1 outbreak in China. Enayati and Özaltın (2020) derive an optimal vaccine distribution policy with the consideration of a "quality guarantee". By building a computation-based optimization model, the authors conclude that the optimal decision of influenza vaccine distribution should be based on "group-specific transmission dynamics". Mehrotra (2020) adopts a stochastic programming model to investigate the optimal ventilator allocation and sharing problem during a pandemic. Exploring several cases in the US, they propose to appoint a central agency to be a coordinator because this can substantially improve the system efficiency by sharing resources in shortage. Besides, some prior studies investigate emergency resources rather than just focusing on healthcare resources alone. For instance, Liu and Zhao (2012) propose an optimization model based on a "dynamic and multi-stage programming" problem to derive the optimal allocation policy for all kinds of emergency resources facing uncertain demand. Mishra and Singh (2022) model a supply chain by using a "mixed-integer nonlinear programming approach". They find the optimal production and allocation policy under a pandemic.

Availability of real data is always of great significance to determine the optimal resource allocation facing a pandemic. Many prior studies have pointed out this fact. For example, De Treville et al. (2006) conduct a real case study of not-for-profit (NFP) operations for a drug facility planning problem. They uncover that lead-time reduction can be an effective way for the NFP organizations to well distribute their resources to improve the supply chain operations as well as save valuable human lives. Cohen et al. (2018) conduct a detailed global field case study of manufacturing sourcing decisions. The authors focus on study trade-offs and the associated risks. They propose the use of "industry clusters" as a possible allocation strategy in global manufacturing. Van der Laan et al. (2016) acquire and analyze the standardized consumption data from more than two thousand medical items consumed in 2013. The authors empirically examine the demand prediction and optimal order planning problem and identify the key factors that will influence the performance. To provide effective planning of "logistical supply chains" for a developing economy during epidemic outbreaks, Anparasan and Lejeune (2018) collect detailed data for the 2010 cholera outbreak in Haiti. They construct a robust "data-driven allocation" model for estimating the optimal emergency medical response. After that, based on a collected real-world data, Anparasan and Lejeune (2019) further establish an epidemic response model and propose a novel algorithmic procedure to help NFP parties to make optimal operational decisions. In their optimal operational plan, critical decisions, such as "healthcare triage" capabilities, distribution needs, and requirements for medical staff, etc., are made.

Three studies in the literature focus on deriving the decision supporting tool for resource allocation problems related to healthcare/diseases. To be specific, Lee et al. (2006) develop a decision-supporting tool called "RealOpt", which includes different exact algorithms as well as fast heuristics, to determine the optimal allocation for vaccines. Ramirez-Nafarrate et al. (2021) propose a novel flexible algorithm to help formulate the location-allocation optimization problem with both capacity and time constraints. In their model, a penalty function is carefully considered for leveraging the associated resources. Realizing the food assistance crisis under the COVID-19 pandemic in the United States, Blackmon et al. (2021) try to develop a decision support system to support the "Farmers to Families Food Box program", aiming at facilitating the food allocation and distribution process between suppliers (or distributors) and farmers.

A few papers use the game-theoretical approach for studying resource allocation problems in supply-side operations. First, Sun et al. (2009) analytically investigate the "optimal stockpile allocation strategy" for different countries by constructing a multiple-period model. Their analytical results show that if the disease's infection rate between countries is low, countries are suggested to agree on an optimal allocation scheme so that an all-win situation will be attained; while if it is unattainable, some countries may have to sacrifice a part of their population to minimize the total infected number, which raises very serious ethical issues. Second, McCoy and Johnson (2014) build an analytical model to study the optimal epidemic control problem. The authors integrate the clinic's capacity decisions with the epidemic control rule. Their findings imply that public health can be improved significantly by incorporating "adherence" into the optimal clinic plan. Besides, clinics are recommended to allocate their budgets across periods to lower the cost. Third, Ivanov (2022) designs a viable supply chain model for proper supply-demand matching that is integrated with three important aspects, namely "agility, resilience, and sustainability". The authors especially highlight the importance of being resilient as it can guarantee the viability of the supply chain system in the future.

2.2.3 Transportation issues

Under the outbreak of epidemics, individuals are less willing to take public transport as they may be infected and also spread the virus. At the same time, some governments impose policies to intervene in transportation to control the pandemic. As a result, the public transportation system and logistics operations in supply chains are facing huge challenges under pandemics such as COVID-19. So far, several studies have examined logistics and transportation topics in the case of pandemics. For example, to assess the impacts of commercial air travel on the Ebola virus spreading, Bogoch et al. (2015) analyze the empirical data from "International Air Transport Association" and study the flight schedules in 2014. Based on the analysis results, the authors suggest using non-commercial flights for shipping essential materials, which not only can help maintain crucial supplies but also mitigate the high risk of having an international infection. Bóta et al. (2017) propose a "vehicle trip network" model to dynamically simulate different kinds of disease outbreak scenarios. By using the real case and data of Twin Cities, they validate and prove that their proposed model is very effective and robust. Kaplan (2020) discusses analytical modeling approaches to capture the effects of COVID-19 on different key business operations issues. The author finds that countries' lockdown restrictions for transportation may not be as effective as they seem to be because they cannot completely mitigate the infections. Instead, the author proposes that an aggressive community screening should be a more efficient way to end the outbreak. Motivated by a real case in Hong Kong, Choi (2020) analytically evaluates the innovative "bring-service-near-your-home" model under COVID-19. The author explores how logistics (offering services on a truck) and technologies can help to support this new business model to combat the operations challenges brought by COVID-19. In particular, the author suggests that the government could adopt various subsidy programs to help improve the supply chain performance if technologies such as blockchain are known to be helpful while companies lack resources.

We synthesize all the important review findings into an innovative research framework of SCM under the pandemic in Figure 2-1, which highlights the key issues of SCM under the pandemic from both demand and supply sides in different pandemic stages. It is clear that supply chain resilience is the major outcome of SCM for the dur-pandemic stage.

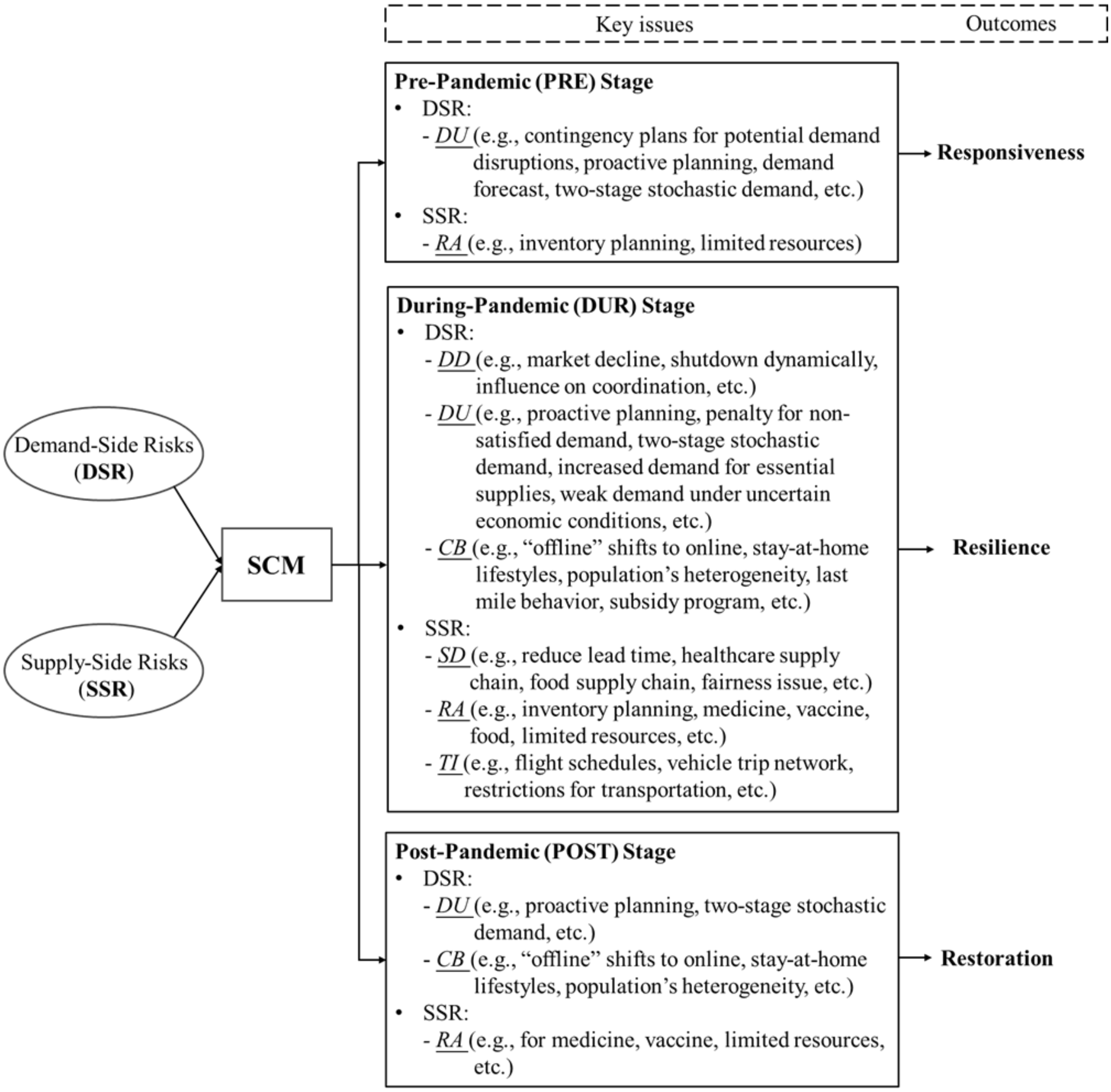

Figure 2-1. A research framework of SCM under the pandemic
(P.S.: See Table A2-1 in Appendix A for the meanings of notations).

2.3 Research Gaps

Based on the proposed framework, we identify several interesting and important research gaps between the current state of knowledge reported in the literature and the proposed framework, which are listed below and summarized in Table 2-1.

Table 2-1. Summary of prior literature and research gaps.

	Prior Literature	**Research Gaps**
Key issues	More research on the supply-side than the demand side (e.g., Chen 2013, Ekici et al. 2014, Cui et al. 2021). Demand-side research does not focus on responsiveness (e.g., Liu et al. 2021).	(i) Less attention on demand-side risk. (ii) Ignoring the potential increase in demand under government subsidies.
	Focus on one side only (e.g., Rachaniotis et al. 2012, Long et al. 2018, Chundakkadan et al. 2022).	(i) Lack of multiple issues. (ii) Lack of combination between OM problem and social issues.
Outcomes	Focus on the resilience of supply chains (e.g., Ivanov 2020, Ivanov and Das 2020).	Neglecting the significance of responsiveness and restoration.
Industries	Focus on the healthcare industry and does not sufficiently highlight how pandemic affects mask supply chains (e.g., Chen 2013, Govindan et al. 2020, Mehrotra et al. 2020).	Very few industries are being explored.
Method	Analytical, computational, and simulation studies dominate. Four organizational theories are applied in empirical research.	Lack of empirical research with different mainstream theories.

Demand-side risk: As summarized in Table 2-1, relatively fewer prior studies focus on the potential risks brought by the demand-side than by the supply side. However, in real-world cases, demand-side risks are crucial in global supply chain management. In particular, under the COVID-19 pandemic, global markets are being confronted with extremely high volatility and uncertainty, which will adversely affect global supply chains in both the short-term and long-term (Asian and Nie 2014). In real-world cases, government subsidies play an important role in helping or even increasing market demand while it is seldom explored in the literature dealing with pandemics. Besides, a recent survey by PwC reveals that consumer behavior is being reshaped (e.g., working from home, buying more essentials, spending more time on entertainment, and preferring shopping online) due to the public health concerns and global economic crises, and it could have long-lasting effects (PwC 2020). We hence believe that it is imperative and even urgent to emphasize the risks from the demand side under a pandemic.

Multiple issues: Understandably, the impacts brought by COVID-19 should not be single-sided (i.e., not just focusing on the demand-side or supply-side). Even though several prior studies have already included multiple issues in their research, the integration of different issues is still far from being comprehensive enough. For instance, there is no study combining the resource allocation problem with consumer behaviors that are critical under COVID-19. We understand that the reason maybe because it is too complicated in analytical modeling analyses to fully consider strategic consumer behaviors. However, we trust with proper model simplification in other aspects as well as trying alternative analysis methodologies, this issue can be overcome. Similarly, we surprisingly notice that there is no prior research considering both demand uncertainty and consumer behavior simultaneously in the case of a pandemic. While actually, the combination of these two issues is common to see in OM research (e.g., Aviv and Pazgal 2008, Hu et al. 2016). Thus, we aim to fill the research gap by combining and investigating multiple issues (especially including consumers behavior) under a pandemic.

Besides, inspired by Cui et al. (2022), we believe that combining the OM problem with social issues (such as workers' welfare, non-governmental organizations) under the pandemic should be emerging topics. This can benefit social welfare and facilitate the long-term development of global supply chains.

Widen the scope of industries: According to the review findings, the scope of the industry being explored in the OM literature under pandemic is relatively narrow, i.e., focusing on healthcare industry. This is especially true for the issue of resource allocation, as the majority of studies put their emphasis solely on the healthcare industry such as vaccine and medicine supply chains. There is no denying that the healthcare industry should be crucially important under pandemics, but real-world observations indicate that almost all the industries are facing challenges under COVID-19. Hence, OM researchers still need to set sights on some other industries such as the retailing industry, which is also significantly influenced by the COVID-19 pandemic.

Note that, most of these research gaps will be explored and bridged in subsequent chapters of this PhD thesis. Especially, we will investigate the OM problem with social issues under the consideration of (i) consumer's changing behavior in retailing industry, (ii) government's subsidy scheme in mask production, and (iii) government's vaccine ordering strategy under both demand and supply side risks.

Chapter 3 Seeking Survivals under COVID-19: The WhatsApp Shopping Service Operations[4,5]

As we reviewed in Chapter 2, there is less research on demand-side risks (e.g., consumers change of behavior) in the literature of SCM under the pandemic. The corresponding social issues are also under explored. We hence conduct this analytical study in Chapter 3, which figures out the impacts of consumer's reshaped behavior on retail service operations and investigates the value of WhatsApp shopping service operations adoption in helping the company to survive the pandemic and enhancing social welfare.

3.1 Problem Description

3.1.1 Research Background

During the COVID-19 pandemic, physical store operations suffer a lot. During the times when people are warned to stay at home with government offices and schools all closed, retail businesses are facing an unforeseeable and unimaginable challenge (Pournader et al. 2020, Choi 2021a, Mitręga and Choi 2021, Xu et al. 2023b). In Hong Kong, a recent report shows that retail business dropped by one third for the first half of 2020 (Hong Kong Business, 2020). Owing to the pandemic, lots of fashion brands, like Topshop, Victoria Secrets, Prada, LV have closed or planned to close shops all over the world (Chen, 2020). It is hence important for retail firms to adapt the changes and seek new ways to survive the pandemic.

Timberland is an internationally famous fashion brand, which possesses an image of "English heritage". Similar to other brands, Timberland definitely faces high pressure under the COVID-19 pandemic period. Timberland Hong Kong's sales volume mainly relies on bricks-and-mortars stores even though it does have its official sales website. This is quite common in crowded cities like Hong Kong as consumers enjoy window shopping and it is easy and convenient to shop in the "normal days". From social media advertisement such as Facebook, it is interesting to note that Timberland Hong

4 A part of this chapter has been published in: "Xu, X., Siqin, T., Chung, S.H., Choi, T.M. 2021. Seeking survivals under COVID - 19: The WhatsApp platform's shopping service operations. Decision Sciences, published online: 10.1111/deci.12552."

5 The notations used in this chapter are self-contained and only valid for this chapter.

Kong has launched the "WhatsApp Shopping Service Operation" (WSO) recently. Unlike the traditional online selling strategy, WSO refers to an innovative selling strategy that allows salespeople to sell physical stores' products to consumers via direct communication on WhatsApp. It relies on physical stores and the staff members there (Choi and Sethi, 2021). Specifically, Timberland Hong Kong offers WSO to "the designated stores", which represent most of the stores in major plazas. Moreover, WSO is available during business hours only. Obviously, it is an innovative strategy to allow consumers to buy via sending WhatsApp messages to the individual stores. Salespeople in the stores will check consumers' requests and orders and then provide recommendations. It is very manual-based, while fits the "fashion boutique" style in which consumers commonly treasured salesperson's advice and services, especially the ones they know well (Goff et al., 1997). Using WhatsApp as the means of ordering also allows more flexible time for the staff members to check inventory and provide advice, without jamming all the phone lines. Details of products (photos, price, etc.) can also be conveniently shared and discussed. WSO is not the "patent" for Timberland Hong Kong. A multitude of brands including The North Face, Terre Bleue, and FILA, etc., have launched WSO for consumers all over the world.

Note that, WSO is strikingly different from traditional online channels from the perspectives of engagement of physical stores and salespeople. WSO is an approach, which offers a chance for physical stores to combat the impacts brought by COVID-19. Comparing with traditional online channels (e.g., the official website and third-party platforms), WSO highly depends on the service provided by salespeople in physical stores. This feature is attractive. From the consumers' side, by chatting with salespeople through WhatsApp, they can experience almost the same service from physical stores without fears of infection. As a result, WSO would provide a service level higher than the one provided by the traditional online channel (Omar et al. 2021). From the firm's side, the implementation of WSO enables physical stores to (i) keep businesses in physical stores and (ii) let salespeople continue to work, even when there is no consumer visiting the physical store.

Unemployment is a serious social problem, which is getting increasingly worse during COVID-19. It is reported that the US unemployment rate has risen sharply from 3.8% in February 2020 to around 15% in May 2020 (Kochhar, 2020). Under this circumstance, the whole society and government are desperate for firms to take more social responsibilities and focus on the issue of workers' welfare. Consequently, seeking a way to maintain the employment level and offset consumer's concerns about COVID-19 is the biggest challenge faced by firms with social welfare in mind (Choi, 2021b). Specifically, firms should pay attention to general welfare of the people (e.g., consumer and workers' welfare) so as to achieve sustainability and bear the needed social responsibility under the COVID-19 pandemic (Lee, 2021). Luckily, owing to the engagement of physical stores and salespeople, WSO can be an efficient way to help firm resolve these problems in some extent. However, it requires firms to have a deep understanding of the impacts of COVID-19 on the firm's operations decisions (e.g., pricing, employment level), profit, consumer welfare as well as workers' welfare (Feng et al., 2022). In this study, we examine the impacts of COVID-19 and explore the values of WSO on firm's operations, aiming to provide useful managerial insights for the firm to combat the challenges mentioned above.

Our work exactly is close to three streams of OM studies: (i) multi-channel operations, (ii) workers' welfare in OM, and (iii) operations strategy under COVID-19. Multi-channel operations have been well adopted in the industry with the development of e-commerce and m-commerce in recent years (Schoenbachler & Gordon 2002, Tsay & Agrawal 2004, Zhang et al. 2017, Wang et al., 2020b), which is especially important to discuss under the pandemic, as it can improve the firm's efficiency when facing demand uncertainty (Chopra et al. 2021). Workers' welfare is unattended when the social environment is stable; however, in turbulent environments (e.g., during COVID-19 pandemic), firms face immediate intense pressure to take social responsibilities and pay more attention to workers' welfare (Freeman & McVea 2001, Huq et al. 2016, Choi and Sethi 2021). In this study, we follow Benjaafar et al. (2022) to consider workers' welfare related to their wages; while differently, we explore under a totally different context of COVID-19 pandemic and WSO. Operations strategy under COVID-19 is a relatively new topic, which is still under-explored; only a few papers have worked on it (e.g., Choi 2020, Singh et al. 2020, Craighead et al. 2020, Bag et al. 2021) and none of them pay attention to the welfare in firms' multi-channel operations, which is critically important under COVID-19. This work aims to bridge this research gap.

3.1.2 Research Questions and Contribution

Motivated by the real case on WSO in Timberland Hong Kong and various other retailers as a measure to cope with COVID-19, we theoretically explore the respective real-world operations. We analytically consider three models, namely the model without COVID-19 and the firm operates a pure physical store (Model PPS), the model with COVID-19 and the firm operates a pure physical store (Model PPS-C), and the model with COVID-19 and the firm operates WSO (Model WSO). We attempt to answer the following research questions.

1. What are the impacts of COVID-19 on the firm's physical store operations? What are the values of WSO for the multiple-channel firm amid COVID-19?
2. How to improve the performance of WSO adoption in terms of the firm's profit and social welfare?
3. Extending the model analyses to the cases when (i) consumer types are endogenous, (ii) the firm endogenously decides service level, and (iii) the firm is WCC-welfare-oriented, will the main findings remain valid?

Based on a standard consumer utility based model, we derive the firm's optimal pricing and employment level decisions by maximizing the firm's profit under three cases, namely Models PPS, PPS-C, and WSO. We first verify the inevitable damages caused by COVID-19 to the firm's physical store operations. Then, we interestingly uncover that, when the firm makes a centralized decision for both "WSO/online" and "offline" operations, WSO is superior to traditional online channels (e.g., the official website) in terms of keeping business under COVID-19, which shows the significance of this new business mode. Besides, we find that the implementation of WSO can stimulate demand in the physical store channel when consumers have a higher fear of infection. This finding is counter-intuitive as the conventional wisdom may suggest that WSO will snatch the demand of physical stores as a portion of consumers will switch to purchase through WSO. While in fact, the high consumers' fear of infection prompts the firm to improve its total service level when implementing WSO, which eventually stimulates the demand for the whole firm (which includes the physical store). This result highlights the significance of implementing WSO as it can help eliminate the demand reduction in physical stores caused by COVID-19.

However, WSO implementation is not always recommended for the firm in terms of increasing profits and social welfare; whether it is valuable to adopt WSO depends on both consumers' fear of infection and consumer type's distribution. We define the profit-welfare-improvement (PWI) outcome for the case in which both the firm's profit and Worker-Consumer-Company (WCC) welfare can be improved simultaneously. Our results show that the PWI outcome can be only achieved when the consumers' fear of infection is moderate and there are more WSO type consumers in the market. Particularly, when the consumers' fear of infection is moderate while there are fewer WSO type consumers in the market, we suggest the government to adopt an incentive mechanism (e.g., providing a subsidy) to support the firm's WSO implementation, which can be an effective way to help the firm survive COVID-19 as well as improve WCC welfare. However, when the consumers' fear of infection is polarized (i.e., extremely low or high), WSO is never recommendable.

3.2 Interview and Primary Data

This OM study is motivated by the real practices from Timberland Hong Kong. In constructing the theoretical model and discussion of findings, close attention is paid to the corresponding operations details. We have also talked to the salespeople of Timberland Hong Kong to learn more of the details and hence this research is not solely theoretical, but also very practical. The analysis also follows the mainstream OM literature with robustness testing. Of course, similar to other analytical OM studies, we do make various common assumptions in constructing the models (e.g., the consumer utility function) and hence we also admit the respective limitations.

Specifically, we conducted two open-ended interviews with salespeople, who are responsible for the WhatsApp shopping service, in two different stores in Hong Kong through WhatsApp (P.S.: The interview guide and original data are provided in Appendix C). One of the interviews was conducted by indicating our research intention (V City Tuen Mun store), while the other was conducted when we were consumers (Tuen Mun Plaza store). Through the open-ended interviews and discussions, we aim to investigate the (i) changes that COVID-19 brings to Timberland retail stores, (ii) changes that the WhatsApp shopping service brings to Timberland retail stores, and (iii) details of the operations for the WhatsApp shopping service including the launching time and approach. In the following, we summarize the interview content with salespeople in two different stores in Table 3-1. The interview results basically validate our observations of industrial practice and model settings. In particular, we note that WSO is a reactive action to cope with COVID-19.

Table 1-1. Interview results.

Objectives	**V City Tuen Mun store**	**Tuen Mun Plaza store**
1. Changes that COVID-19 brings to salespeople, consumers, and physical stores.	- Salespeople started to sell products through WhatsApp. - Fewer consumers visit the physical store due to the fear of infection. - The physical store is seriously	- Salespeople started to sell products through WhatsApp. - Consumers can purchase products without going to the physical store. - One of the reasons for physical

	affected.	stores to adopt the WhatsApp shopping service is COVID-19.
2. Changes that WhatsApp shopping brings to salespeople, consumers, and physical stores.	- Salespeople provide service to consumers through WhatsApp. - Physical stores have the other approach to sell products.	- Salespeople make recommendations to consumers by taking pictures and sending official website links. - Consumers have the other choice for purchasing from the Internet. - The physical stores pay for the delivery cost.
3. When to implement WhatsApp shopping?	After COVID-19 pandemic.	After COVID-19 pandemic.
4. Where do the salespeople provide service to WhatsApp consumers?	In the physical store.	In the physical store.

3.3 Analytical Model: Basic Model

We consider a firm that employs y salespeople to provide services and sells the product with a unit retail price p. The unit service level of each salesperson is exogenously given by s. (P.S.: We provide the meaning of notations, subscripts, and superscripts used in this chapter in Table 3-2) This setting captures the fact that many retail brands tend to set a fixed standard for sales service based on their operations principles. For example, Uniqlo has its standard-format for consumer services (e.g., standard service skills) (Fast Retailing Annual Report 2007). In our own discussions with the industry, the same situation is commonly noted in many department stores and retailers. We will relax this assumption and consider the case in which the firm decides unit service level endogenously in the extended model analysis (Chapter 3.5). The firm's total service level that can be realized is given by $T = ys$, which means that the total service level is measured by the employment level and service level of each salesperson. This setting is reasonable because when more salespeople are present, quicker service responses in both the physical store and WhatsApp can be achieved. To improve the total service level, the firm needs to bear a cost $IC(T)$. This service improvement cost follows an increasing convex function, and hence we have $IC^{'}(T) > 0$ and $IC^{''}(T) > 0$. The increasing convex property reflects that the cost increases when the marginal service level is improved, and it is costly for the firm to seek higher and higher improvement of service level. For tractability, we follow the literature (such as Li and Wan (2017)) to consider $IC(T) = \lambda T^2 = \lambda(ys)^2$ in the following analysis, where $\lambda > 0$ is the coefficient of service improvement cost. The salespeople's wage is comprised of two parts: (i) a fixed wage f for each person, and (ii) a piece-rate wage β depending on the demand. Note that, this setting is consistent with the real-world practice based on our interview results. As we mentioned in the introduction, it is the firm's responsibility to achieve social sustainability (including both the consumer and workers' welfare) under the COVID-19 pandemic. Here, pricing affects consumer welfare and staffing influences workers' welfare. So, it requires the firm to make careful decisions on both pricing and employment level, which are two factors directly influencing the consumer and workers' welfare in operations. Hence, in our model, we suppose that the firm initially sells its product through physical stores purely, while having the choice to conduct WSO (or not) under the COVID-19 pandemic; then, the firm decides the retail price p and employment level (i.e., no. of salespeople) y simultaneously to maximize its profit with the consideration of unit production cost c.

The market size is normalized to be 1. Consumers are heterogeneous in their valuation v for the product, which is drawn from a uniform distribution: $v \sim U[0, 1]$. They make purchasing decisions based on their utilities, which depends on the price p, total service level sy, and other considerations under different scenarios. For instance, consumers will receive a fear of infection ξ when going to physical stores under COVID-19, while having a trust discount t when shopping through WSO because of unfamiliarity and concerns (e.g., information privacy concerns, authenticity concerns, etc.) during shopping under WSO. We hence classify two types of consumers called "store type" and "WSO type" corresponding to features of consumer's concerns accordingly. Similar to Nageswaran et al. (2020), our basic model assumes that a consumer is of the WSO type with an exogenously given proportion θ, which captures consumers' inherent preference for one mode of shopping (over the other) with a particular firm, and $\theta \in [0,1]$. We will further explore the case in which θ is endogenously determined in the extended model in Chapter 3.5. If a consumer does not purchase the product, the utility is zero. In our study, we consider that the firm first decides the selling price and the employment level simultaneously, and then consumers make their purchasing decisions according to their utilities.

Before proceeding with deeper analysis, we propose the novel concept of Worker-Consumer-Company (WCC) welfare, which is defined as the summation of the firm's profit π, consumer surplus CS, and workers' welfare WW. We regard WCC welfare as an important indicator that can be used to reflect the firm's social welfare performance with the special consideration of workers' welfare (Benjaafar et al., 2022). This concept is especially crucial under the outbreak of COVID-19, as in such a turbulent environment, the firm faces intense pressure to take corporate social responsibilities and should focus more on workers' welfare (Freeman and McVea, 2001; Huq et al., 2016). Then, in order to reveal how COVID-19 pandemic and the new WSO mode would affect the firm's operations performance, we explore the following three cases in our basic model: (i) without COVID-19 and the firm operates a pure physical store (Model PPS), (ii) with COVID-19 and the firm operates a pure physical store (Model PPS-C), and (iii) with COVID-19 and the firm operates WSO (Model WSO).

Table 2-2. List of notations in Chapter 3.

Notation	**Meaning**
y	Employment level.
s	Unit service level that can be provided by each salesperson.
λ	Coefficient of the service improvement cost.
f	Fixed wage for each salesperson.
β	Piece-rage wage depends on the product's demand.
p	Product's unit retail price.
c	Product's production cost.
v	Consumer's valuation on the product, $v \sim U[0,1]$, where $U[0,1]$ stands for the uniform distribution with bound from 0 to 1.
ξ	Consumer's fear of infection for physical store shopping.
t	Consumer's trust discount for shopping through WhatsApp.
θ	Proportion for consumer inherently is of WSO type.
k	Consumer's sensitivity to the sales service for store shopping.
l	Consumer's sensitivity to the sales service for WhatsApp shopping.
g	The unit delivery cost of each demand generating from WhatsApp shopping.
H	The ceiling of service level improvement cost in Robustness Checking 2.
α	The weight of profit in WCC welfare in Robustness Checking 3.
T	Total service level provided to the consumers, where $T = sy$.
π	Firm's total profit.
CS	Consumer surplus.
WW	Workers' welfare, i.e., salespeople's total income.
WCC	Worker-Consumer-Company welfare, where $WCC = \pi + CS + WW$.

Remarks: The subscripts "PPS" and "WSO" denote the pure physical store and WhatsApp channels, respectively; The superscripts $\overline{COV}$ and COV denote the case without and with COVID-19 pandemic, respectively.

3.3.1 Model PPS

Without COVID-19 (denoted as $\overline{COV}$), the firm usually sells its product through the pure physical store. The consumers make their purchasing decisions based on utility function: $U_{PPS}^{\overline{COV}} = v - p + ksy$, where k represents consumer's sensitivity to the sales service for store shopping. Note that, this linear utility function which is decreasing in selling price and increasing in total service level is commonly used in the service operations literature, e.g., Tsay and Agrawal (2000), Hua et al. (2016), etc. The consumers will make the purchase when they receive a positive utility, i.e., $U_{PPS}^{\overline{COV}} > 0$, otherwise, they will buy nothing. Hence the demand under Model PPS can be realized as $D_{PPS}^{\overline{COV}} = \int_{p-ksy}^{1} \psi(v)\, dv = 1 - p + ksy$, where $\psi(\cdot)$ is the standardized normal probability density function. Thus, the firm's total profit is:

$$\pi_{PPS}^{\overline{COV}}(p, y) = (p - c - \beta)(1 - p + ksy) - \lambda s^2 y^2 - fy,$$

which is equal to the total income of physical stores minus the total operations costs (i.e., service improvement cost and salespeople's wage).

Under Model PPS, the consumer surplus ($CS_{PPS}^{\overline{COV}}$), workers' welfare ($WW_{PPS}^{\overline{COV}}$) and WCC welfare ($WCC_{PPS}^{\overline{COV}}$) are respectively given as follows:

$$CS_{PPS}^{\overline{COV}} = \int_{p-ksy}^{1} (v - p + ksy)\psi(v)\, dv = \frac{1}{2}(1 - p + ksy)^2;$$

$$WW_{PPS}^{\overline{COV}} = fy + \beta D_{PPS}^{\overline{COV}} = fy + \beta(1 - p + ksy);$$

$$WCC_{PPS}^{\overline{COV}} = \pi_{PPS}^{\overline{COV}} + CS_{PPS}^{\overline{COV}} + WW_{PPS}^{\overline{COV}}.$$

Note that, in all the following analyses, we consider the case when $\lambda > \frac{k^2}{4}$, which means that service improvement is costly, and it is infeasible to increase the service level indefinitely. This assumption is reasonable as in practice, improving service level usually incurs a non-trivial and sufficiently high cost, e.g., investment in resources (Xia et al., 2017). Having this assumption also ensures the concavity of the firm's profit function. By maximizing the firm's total profit, we derive Lemma 3.1.

Lemma 3.1. *(i)The firm's optimal retail price and employment level are* $p_{PPS}^{\overline{COV}*} =$

$\frac{s[(2\lambda-k^2)(c+\beta)+2\lambda]-fk}{s(4\lambda-k^2)}$ *and* $y_{PPS}^{\overline{COV}*}=\frac{ks(1-c-\beta)-2f}{s^2(4\lambda-k^2)}$, *respectively. (ii)* $D_{PPS}^{\overline{COV}*}\geq 0$ *if and only if* $\beta\leq\beta_{PPS}^{\overline{COV}}$, *where* $\beta_{PPS}^{\overline{COV}}=1-c-\frac{fk}{2s\lambda}$.

Lemma 3.1(i) presents the optimal decisions for the case without COVID-19, by setting which the firm can earn its maximum profit. From Lemma 3.1(ii), we find that the demand is positive if and only if the salesperson's piece-rate wage is not too high; in other words, the firm will lose all the business if it pays a sufficiently high piece-rate wage to salespeople. This is because the firm tends to reduce the employment level of the salesperson if the payment is high, which will drive away consumers because of the low total service level.

3.3.2 Model PPS-C

We consider the case in which the firm still operates a pure physical store under the COVID-19 pandemic (denoted as COV). In this scenario, the consumers who go to the physical store and make the purchase will get a fear ξ due to the pandemic[6]. Here, ξ refers to the fear of infection, which makes the consumers avoid accessing the public places under the pandemic (Lazzerini et al., 2020). This setting is also consistent with our interview results which show that fewer consumers visit the physical store after COVID-19 (see Table 3-1). Thus, consumer utility can be realized as $U_{PPS}^{COV}=v-p+ksy-\xi$, and the corresponding demand is $D_{PPS}^{COV}=\int_{p-ksy+\xi}^{1}\psi(v)\,dv=1-p+ksy-\xi$. Consequently, the firm's total profit is:

$$\pi_{PPS}^{COV}(p,y)=(p-c-\beta)(1-p+ksy-\xi)-\lambda s^2y^2-fy,$$

consumer surplus is:

$$CS_{PPS}^{COV}(p,y)=\int_{p-ksy+\xi}^{1}(v-p+ksy-\xi)\psi(v)\,dv=\frac{1}{2}(1-p+ksy-\xi)^2,$$

and workers' welfare is:

$$WW_{PPS}^{COV}=fy+\beta D_{PPS}^{COV}=fy+\beta(1-p+ksy-\xi).$$

The corresponding WCC welfare is hence given as follows:

$$WCC_{PPS}^{COV}=\pi_{PPS}^{COV}+CS_{PPS}^{COV}+WW_{PPS}^{COV}.$$

We derive the optimal decisions and summarize them in Lemma 3.2.

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[6] Note that, the salespeople may also have fear of infection, while no matter whether they possess high or low fear of infection, they have no choice but to work in stores; or they will face unemployment, which should not be a preferable choice for workers (in a place like Hong Kong or Japan). Hence, in the context of this research, we do not consider it as a driving factor.

Lemma 3.2. *(i) The firm's optimal retail price and employment level are* $p_{PPS}^{COV*} = \frac{s[(2\lambda-k^2)(c+\beta)+2\lambda(1-\xi)]-fk}{s(4\lambda-k^2)}$ *and* $y_{PPS}^{COV*} = \frac{ks(1-c-\beta-\xi)-2f}{s^2(4\lambda-k^2)}$*, respectively. (ii)* $D_{PPS}^{COV*} \geq 0$ *if and only if* $\beta \leq \beta_{PPS}^{COV}$*, where* $\beta_{PPS}^{COV} = 1 - c - \xi - \frac{fk}{2s\lambda}$*, which is smaller than* $\beta_{PPS}^{\overline{COV}}$ *and decreasing in* ξ*.*

Same as the results derived in Lemma 3.1, we find that if the piece-rate wage for salespeople is sufficiently high, the firm will lose all its business. Particularly, note that the maximum piece-rate wage under pandemic is lower than the one in the case without pandemic (i.e., $\beta_{PPS}^{COV} < \beta_{PPS}^{\overline{COV}}$). It means that the firm is more likely to lose all the business under the COVID-19 pandemic. We hence infer that COVID-19 pandemic is detrimental and even fatal to the firm's physical store operations. That is the reason why so many brands have decided to close up their physical stores during the outbreak of COVID-19. Hong Kong expects 1/4 of retail stores to close by the end of 2020 (Staff, 2020). The fashion retailer Inditex claimed to close as many as 1,200 stores over the next two years (Chaudhuri, 2020); *H&M* planned to cut 250 of its stores globally (BBC News, 2020). Our results provide a theoretical basis for these practical observations.

3.3.3 Model WSO

When facing COVID-19 pandemic, the firm has a choice to conduct WSO, by using which the consumers can enjoy the sales services by chatting with salespeople through WhatsApp and make purchases without fear of infection. Nevertheless, since WSO is a relatively new sales mode, the consumers who make the purchase through WSO will have a trust discount t for using it. Besides, this trust discount captures consumer's concern of purchasing without physically touching the products (Zhang et al. 2017), which will directly reduce consumers utility. Hence, the utility function for those consumers buying through WSO is $U_{WSO} = v - p + lsy - t$, where l represents consumer's sensitivity to the sales service for WhatsApp shopping. For simplicity, we let $l = k$, which implies that the store type and WSO type consumers are homogeneous in the sensitivity of service level. This assumption is reasonable in the context of WSO, as the services are provided by the same group of salespeople in both the physical store and WSO; hence the consumers are likely to possess the same expectation for the service levels. Recall that a proportion θ of consumers is of WSO type, and the remaining $(1-\theta)$ are store type. Hence the total demand can be realized as $D_{WSO} = (1-\theta)D_{PPS} + \theta\int_{p-ksy+t}^{1}\psi(v)\,dv = (1-\theta)(1-p+ksy-\xi) + \theta(1-p+ksy-t)$, where the first item represents the demand from physical stores, and the second item denotes the demand from WSO. Note that when adopting WSO, the firm usually pays for the unit delivery cost g for each WSO demand. This consideration is based on real-world practices such as what we have observed from Timberland, which provides free shipping for purchasing via WSO. Hence the firm's overall profit is:

$$\pi_{WSO}(p,y) = (p-c-\beta)(1-\theta)(1-p+ksy-\xi) + (p-c-\beta-g)\theta(1-p+ksy-t)$$
$$-\lambda s^2y^2 - fy.$$

Consumer surplus is:

$$CS_{WSO} = (1-\theta)\int_{p-ksy+\xi}^{1}(v-p+ksy-\xi)\psi(v)\,dv + \theta\int_{p-ksy+t}^{1}(v-p+ksy-t)\psi(v)\,dv$$
$$= \frac{(1-\theta)(1-p+ksy-\xi)^2}{2} + \frac{\theta(1-p+ksy-t)^2}{2}.$$

Workers' welfare is:

$$WW_{WSO} = fy + \beta D_{WSO}^{COV}.$$

WCC welfare is:

$$WCC_{WSO} = \pi_{WSO} + CS_{WSO} + WW_{WSO}.$$

We let $\emptyset = (1-\theta)\xi + \theta t$ and obtain Lemma 3.3.

Lemma 3.3. *(i) The firm's optimal retail price and employment level are* $p_{WSO}^* = \frac{s[(2\lambda-k^2)(c+\beta+g\theta)+2\lambda(1-\emptyset)]-fk}{s(4\lambda-k^2)}$ *and* $y_{WSO}^* = \frac{ks(1-\emptyset-c-\beta+g\theta)-2gks\theta-2f}{s^2(4\lambda-k^2)}$*, respectively. (ii)* $D_{WSO}^* \geq 0$ *if and only if* $\beta \leq \beta_{WSO}$*, where* $\beta_{WSO} = 1-c-\emptyset-g\theta-\frac{kf}{2s\lambda}$*. (iii)* $\beta_{WSO}\begin{Bmatrix}>\\=\\<\end{Bmatrix}\beta_{PPS}^{COV}$ *if and only if* $\xi\begin{Bmatrix}>\\=\\<\end{Bmatrix}t+g$.

Lemma 3.3(i) presents the optimal decisions for WSO model, and Lemma 3.3(ii) gives the threshold for a maximum piece-rate wage, exceed which there will be no business for the firm. Although the results are similar to the ones obtained in pure physical store cases (i.e., Lemmas 3.1 and Lemma 3.2), we still obtain some interesting findings in Lemma 3.3(iii). Specifically, we notice that WSO cannot always help the firm to survive COVID-19 pandemic; only when the consumers' fear of infection is relatively large, WSO is effective to help the firm keep business as the firm can afford a higher payment to salespeople and is less likely to lose all the business. This result is understandable as fewer consumers are willing to buy from physical stores with high fear of infection, and which embodies the value of WSO.

Then, we proceed to conduct the sensitivity analysis for optimal decisions, trying to find out how the consumer type distribution will influence the firm's WSO implementation in Proposition 3.1.

Proposition 3.1. *(i)* p_{WSO}^* *and* y_{WSO}^* *are increasing in* θ *if and only if* ξ *is relatively large. (ii)* π_{WSO}^* *is convex in* θ. *(iii)When* $X(t-\xi)<0$, WCC_{WSO}^* *is convex in* θ; *when* $X(t-\xi)>0$ WCC_{WSO}^* *is concave in* θ *if and only if* $\xi \in (t-X_1, t-X_2)$, *where* X_1 *and* X_2 *are two unique roots of equation* $X(t-\xi)=0$, *and where* $X(t-\xi)=(k^4-6k^2\lambda+4\lambda^2)(t-\xi)^2+2g(k^4-6k^2\lambda+4\lambda^2)(t-\xi)+2g^2(k^2-6\lambda)\lambda$. *The characteristic of* $X(t-\xi)$ *is shown below.*

(a) If $\lambda \le \frac{(3+\sqrt{5})k^2}{4}$, $X(t-\xi)<0$ *always holds.*

(b) If $\lambda > \frac{(3+\sqrt{5})k^2}{4}$, $X(t-\xi)<0$ *holds for* $\xi \in (t-X_1, t-X_2)$*; otherwise,* $X(t-\xi)>0$.

Proposition 3.1 captures the impacts of consumer type distribution on firms' WSO decisions and performance. We notice that the consumers' fear of infection is a critically important factor that will influence the firm's decisions. Specifically, if consumers hold a high fear of infection, the high proportion of WSO type consumers will induce the firm to sell high-price products with more salespeople; while if consumers' fear of infection is relatively low, the firm should set a lower price and employ fewer salespeople when there are more WSO type consumers. Thus, the firm needs to make WSO decisions carefully based on both consumer types and their fear of infection.

Then, before we proceed to conduct the analysis of firm's performance, we want to define two different consumer type distributions: (i) *Concentrated distribution*, under which the consumers are concentrated in the same type (i.e., either store type or WSO type); that is, the proportion of WSO type consumers θ is relatively large or small. (ii) *Equal distribution*, under which the segments of two types of consumers are approximately the same, that is, the proportion of WSO type consumers θ is around 0.5 (i.e., moderate). According to Proposition 3.1(ii), we find that the firm's optimal profit is always convex in the proportion of WSO type consumers. It implies that WSO is more profitable for the firm when the proportion of consumers of the same type is higher (i.e., under the centralized distribution), rather than equally distributed. We hence suggest the firm take measures to enlarge the number of WSO type consumers, e.g., advertising more about WSO mode, so as to boost its total profit. Note that, increasing the number of store type consumers is also doable but it is not recommended, as under the COVID-19 pandemic, encouraging more consumers to shop in store should be dangerous and unacceptable. Next, as to the WCC welfare performance, Proposition 3.1(iii) shows that for the firm with a low service improvement cost coefficient, concentrated distribution of two types of consumers is more welcomed; whereas for the firm with high service improve cost coefficient, equal distribution of consumer type could be more advantageous as long as consumers' fear of infection is moderate. The potential reasons are: (i) when the firm's service improvement cost coefficient is relatively low, the firm will improve its total service level by employing more salespeople (i.e., $\frac{\partial y_{WSO}^*}{\partial \lambda} > 0$), which is beneficial to both consumer and workers' welfare; thus, the higher WCC welfare can be achieved as long as the firm can gain a higher profit (refer to Proposition 3.1(iii)). (ii) When the firm's service improvement cost coefficient is relatively high, fewer salespeople will be hired, which is detrimental to consumer and workers' welfare. So, only two ways for the firm to acquire higher WWC welfare are improving consumer surplus by lowering the retail price under extremely low fear of infection, or by enhancing the employment level under extremely high fear of infection (refer to Proposition 3.1(i)). To summarize, we find it is possible for the firm to gain higher profit and WCC welfare simultaneously under WSO case as long as its service improvement cost coefficient is relatively low or the consumers are under concentrated distribution with extremely high or low fear of infection. Our results can also well explain why not all stores of a brand provide WSO. This is because only those stores with a lower cost coefficient have high incentives to implement WSO, otherwise, the brand is less likely to support them to adopt WSO.

3.4 Comparisons and Analysis

In Chapter 3.3, we have derived optimal outcomes for the three cases, i.e., PPS, PPS-C, and WSO; in this chapter, we will proceed to do comparisons among these cases, aiming at evaluating the impacts brought by COVID-19 pandemic on firm's operations, as well as identifying the values of WSO implementation and providing useful implications and guidance for the firm to survive COVID-19.

3.4.1 Impacts of COVID-19

In this subchapter, we do comparisons between cases PPS and PPS-C, by doing which we can identify the impacts of COVID-19 on firm's physical store operations.

Proposition 3.2. *(i)* $p_{PPS}^{COV*} < p_{PPS}^{\overline{COV}*}$ *and* $y_{PPS}^{COV*} < y_{PPS}^{\overline{COV}*}$. *(ii)* $\pi_{PPS}^{COV*} < \pi_{PPS}^{\overline{COV}*}$ *and* $WCC_{PPS}^{COV*} < WCC_{PPS}^{\overline{COV}*}$.

First, Proposition 3.2(i) shows that the COVID-19 pandemic always leads to the price reduction and unemployment. This result is completely in conformity with real-world practices: numerous firms have offered product pricing discounts and laid off their workers in the physical stores during the COVID-19 pandemic. Then, Proposition 3.2(ii) reveals that both firm's profit and WCC welfare will be decreased under the COVID-19 pandemic. This result is intuitive, as the pandemic will curtail consumers' willingness to purchase in the physical store because they are afraid of being infected. Thus, we can easily infer that the COVID-19 pandemic will definitely harm the firm's physical store operations, which desperately requires the firm to take measures to combat these negative effects. So, in the next subchapter, we will examine how WSO can help the firm to improve its performance in perspective of profit and WCC welfare under the COVID-19 pandemic.

3.4.2 Values of WSO Implementation

According to our general knowledge, WSO should be helpful to the firm's operations as consumers can alternatively make purchases from WSO without fear of infection; meanwhile, the firm does not need to employ additional salespeople for WSO. However, every coin has two sides. The unfamiliarity of this new mode of shopping may bring concerns to consumers (e.g., information security concern, authenticity concern, etc.). Besides, the firm usually has to pay the additional delivery cost for each delivery, which increases the cost for each demand. Hence, it is challenging for the firm to balance the trade-offs between the advantages and drawbacks of WSO. In this subchapter, in order to identify the values of WSO implementation on firm's performance under COVID-19, we compare the results obtained in WSO case with the ones in PPS-C, and derive Propositions 3.3 and 3.4.

Proposition 3.3. $D^*_{PPS}\left(p^*_{WSO,}y^*_{WSO}\right)\begin{Bmatrix}>\\=\\<\end{Bmatrix}D^*_{PPS}(p^{COV*}_{PPS}{}^*y^{COV*}_{PPS})$ *if and only if* $\xi\begin{Bmatrix}>\\=\\<\end{Bmatrix}\xi_{PPS}$ *where* $\xi_{PPS}=\frac{2s(1-c-t-\beta+g(1-\theta)+t\theta)\lambda-k\left(f-kst(1-\theta)\right)}{k^2s(1-\theta)+2s\theta\lambda}$.

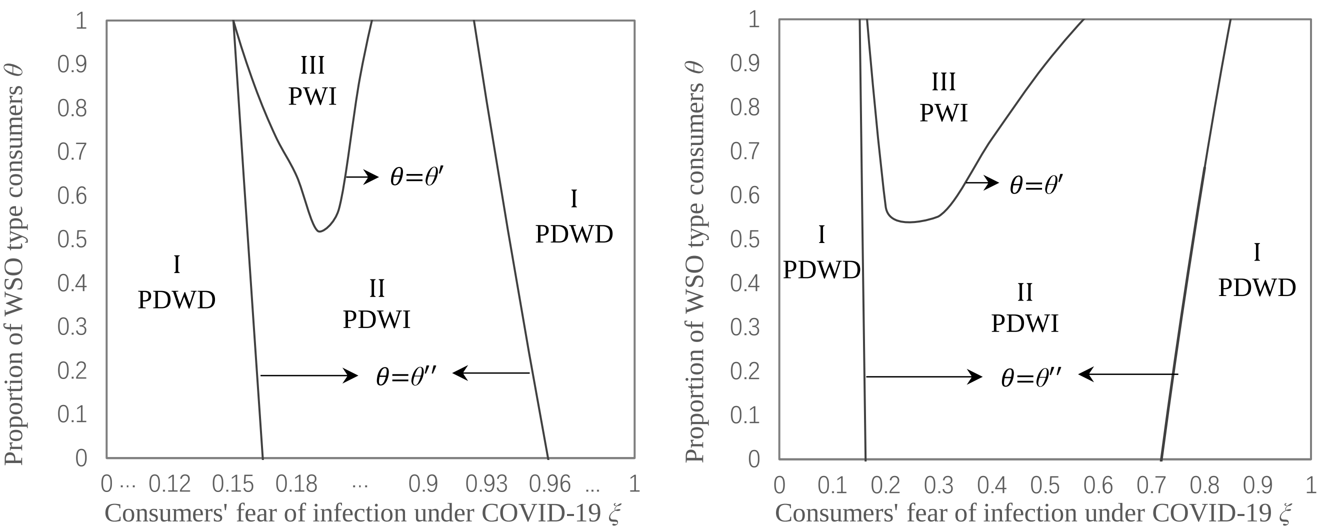
Proposition 3.3 provides an interesting finding, that is, the demand in the physical store can be higher under the WSO case than under the PPS-C case as long as the consumers' fear of infection is relatively large. This result is counter-intuitive as in our common sense, WSO will snatch the demand of physical stores because a portion of consumers will transfer to purchase through WSO instead of going to physical stores. However, our result implies that the implementation of WSO is able to stimulate the demand in the physical store, especially when consumers have a higher fear of infection.

This is because the consumer's high fear of infection prompts the firm to improve its total service level, which eventually stimulates the total demand. This finding is consistent with the real-world observations. Specifically, a recent survey from Latin American Business Stories (LABS) has uncovered that the implementation of WSO has been driving sales and increasing profitability for 53% of brands and companies in Brazil (Fenelon and Torresan, 2021), which shows the great value of WSO implementation for the firm's physical store operations under the COVID-19 pandemic.

Proposition 3.4. *(i)* $p_{WSO}^{*} > p_{PPS}^{COV*}$ *and* $y_{WSO}^{*} > y_{PPS}^{COV*}$ *if and only if* ξ *is relatively large. (ii) When* $0 \leq \xi < \underline{\xi}^{B}$ *or* $\xi > \bar{\xi}^{B}$, $\pi_{WSO}^{*} < \pi_{PPS}^{COV*}$*; when* $\underline{\xi}^{B} \leq \xi \leq \bar{\xi}^{B}$, $\pi_{WSO}^{*} \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} \pi_{PPS}^{COV*}$ *if and only if* $\theta \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} \theta'$, *where* $\underline{\xi}^{B}$ *and* $\bar{\xi}^{B}$ *are the two positive roots of equation* $s\lambda\xi^2 + [fk - 2s(1 - c - \beta)\lambda]\xi - (g + t)(fk - s(2 - 2c - g - t - 2\beta)\lambda) = 0$ *. (iii) When* $X(t - \xi) > 0$, $WCC_{WSO}^{*} > WCC_{PPS}^{COV*}$ *if and only if* $\theta < \theta''$*; when* $X(t - \xi) < 0$, $WCC_{WSO}^{*} > WCC_{PPS}^{COV*}$ *if and only if* $\theta > \theta''$*.*[7]

Proposition 3.4(i) demonstrates the implications of WSO implementation on the firm's decisions. Similar to the findings shown in Proposition 3.1, the consumers' fear of infection is a critical influence factor with respect to the firm's decisions. If the consumers' fear of infection is relatively large, the firm will raise the price and employ more salespeople to increase the total service level for WSO; while if the consumers are less fear of infection, the firm tends to cut down the price and employ fewer salespeople when implementing WSO. Then, by comparing the firm's optimal profits, we find that only when the consumers' fear of infection is moderate and the proportion of WSO consumers is larger than a threshold, the firm can earn more from implementing WSO; otherwise, it is better not to adopt WSO as the total profit will be hurt. Moreover, when it comes to the firm's WCC welfare, we notice that the value of WSO implementation is also jointly influenced by consumer type distribution and their fear of infection. To show a clear picture of this joint impact on the firm's profit and WCC welfare, we depict Figure 3-1 to present the values of WSO implementation.

[7] Please refer to Proposition 3.1 for the characteristic of function $X(t - \xi)$.



(a) When $\lambda > \frac{(3+\sqrt{5})k^2}{4}$,

(b) When $\lambda \leq \frac{(3+\sqrt{5})k^2}{4}$,

Remarks: Region I (PDWD) implies $\pi_{WSO}^{COV*} < \pi_{PPS}^{COV*}$ and $WCC_{WSO}^{COV*} < WCC_{PPS}^{COV*}$; Region II (PDWI) implies $\pi_{WSO}^{COV*} < \pi_{PPS}^{COV*}$and $WCC_{WSO}^{COV*} > WCC_{PPS}^{COV*}$; Region III (PWI) implies $\pi_{WSO}^{COV*} > \pi_{PPS}^{COV*}$and $WCC_{WSO}^{COV*} > WCC_{PPS}^{COV*}$.

Figure 3-1. The value of WSO implementation with respect to the profit and WCC welfare (We let $c = 0.4$, $\beta = 0.1$, $k = 0.25$, $s = 0.9$, $f = 0.05$, $t = 0.05$, $g = 0.1$, and $\lambda = 0.1$ in (a), $\lambda = 0.05$ in (b)).

Figure 3-1 exhibits all the possible relationships for the firm's profit and WCC welfare between case WCC and case PPS-C. Consistent with the results derived in Propositions 3.4(ii) and (iii), we can observe that both the consumer type distribution and their fear of infection will influence the value of WSO implementation significantly. Specifically, when the consumers' fear of infection is moderate, WSO is always valuable to improve WCC welfare, and it is effective to increase profit if the proportion of WSO consumers is relatively large, which is understandable; while when the consumers' fear of infection is extremely large or small, WSO is always disadvantageous for both firm's profit and WCC welfare. This result is counter-intuitive as it is commonly believed that the extremely high fear of infection will prompt more consumers to purchase through WSO, hence the higher value of WSO should be expected. However, in fact, as we have discussed in Proposition 3.4(i), the high fear of infection will result in a price hike for WSO, which eventually cuts the demand as well as harms the firm's WCC welfare. When the consumers' fear of infection is extremely low, it is understandable that both the firm and consumers will prefer the pure physical store operations to WSO. Besides, we notice that when the cost coefficient of service improvement is relatively small (i.e., Figure 3-1(b)) or consumers' fear of infection is relatively low (i.e., left side of the dotted line in Figure 3-1(a)), the firm tends to create a higher WCC welfare under WSO if there are more WSO type consumers; however, when the service improve cost coefficient is relatively large and the consumers' fear of infection is relatively high (i.e., right side of dotted line in Figure 3-1(a)), WSO implementation is more likely to lower the firm's WCC welfare if the most of consumers are WSO type. This is because when both these two influence factors are relatively large, the price of product will be sharply raised under WSO implementation (refer to Proposition 3-1(i)), which damages consumer surplus and consequently result in decreases in WCC welfare.

To summarize, we define three regions, namely PWI, PDWI (profit-decreasing welfare-increasing), and PDWD (profit-decreasing welfare-decreasing), to identify the values of WSO implementation in terms of firm's profit and WCC welfare. In PWI region (i.e., high proportion of WSO type consumers with a moderate fear of infection), it is strongly recommended for the firm to implement WSO as it is beneficial to both profit and WCC welfare. In PDWD region (consumers' fear of infection is extremely low or high), there is completely no incentive for the firm to adopt WSO as the entire performance will be deteriorated. In PDWI region (i.e., low proportion of WSO type consumers with a moderate fear of infection), implementing WSO is effective for the firm to improve WCC welfare while at the cost of losing profit. This should be a tricky case, as the higher WCC welfare is welcomed by the whole society especially under COVID-19, whereas the loss of profit is unexpected for the firm. So, when this case occurs, i.e., $\theta^{''} < \theta < \theta^{'}$, we propose the government to consider adopting an incentive mechanism (e.g., providing a subsidy) to help the firm overcome profit difficulties induced by the implementation of WSO. We have Proposition 3.5.

Proposition 3.5. *Under the COVID-19 pandemic, when* $\theta'' < \theta < \theta'$*, the government can provide a subsidy of* $N > \underline{N}$ *to help the firm achieve the PWI outcome in terms of total profit and WCC welfare, where* $\underline{N} = \frac{\theta[A_1(t-\xi)^2 + A_2(t-\xi) + A_3]}{2s(4\lambda - k^2)^2} > 0$ *and* A_1*,* A_2, A_3 *can be checked in Appendix B.*

Proposition 3.5 indicates a case in which the government has an obligation to conduct an incentive mechanism to support the firm's WSO implementation. This case appears when the implementation of WSO consumer type is equally distributed and their fear of infection is moderate. In this case, the value of WSO implementation is positive for WCC welfare while negative for the firm's profit. For implications, in order to help those firms with higher WCC welfare performance to overcome the financial difficulties under COVID-19, the amount of needed subsidy by the government to support the firm's WSO implementation is presented in Proposition 3.5. The government can hence make reference to it for setting the right amount of subsidy. Such an incentive mechanism, e.g., providing subsidies to help firms survive the pandemic, has been widely considered by governments worldwide during COVID-19. For instance, Japan and Hong Kong have launched subsidy projects to support manufacturers and individual business operators affected by COVID-19; the European Union (EU) and the US have provided a great amount of funding for a broad range of projects to help their citizens and firms survive COVID-19.

We summarize all the important managerial findings derived from the basic model in Table 3-3 as an overview. To sum up, the outbreak of COVID-19 will deteriorate the firm's physical store operations; the well implementation of WSO can be an effective way for the firm to combat the negative effects brought by COVID-19; however, it may also be a "death-blow" if the firm does not make correct decisions. Our implications proposed in this research can help the firm to survive the COVID-19 crisis.

Table 3-3. Summary of managerial findings in the basic model.

	Impacts of COVID-19	**Values of WSO**
Threshold of having "no business"	Lower	Higher if consumers fear more of infection (i.e., ξ is large).
Retail price	Reduced	Increased if ξ consumers fear more of infection (i.e., ξ is large).
Employment level		
Demand in the physical store		
Firm's profit	Harmed	Benefitted if there are more WSO type consumers (i.e., θ is large) and the fear of infection (ξ) is moderate.
WCC welfare		Benefitted under certain conditions (refer to Proposition 3.2(iii) and Figure 3-1)

3.5 Robustness Checking

3.5.1 Endogenous Consumer Types

In the basic model, we consider that the proportion of each consumer type is exogenously given. In this subchapter, we will relax this setting and let consumers decide their type: store or WSO, by incorporating heterogeneity in consumer's value discount for WSO. We suppose the discount t is uniformly distributed from 0 to $\hat{t}$, i.e., $t \sim U(0, \hat{t})$. Recall that, for simplicity, we let $l = k$; the consumer utilities for purchasing in the physical store and through WSO are $U_{PPS}^{COV} = v - p + ksy -$

ξ and $U_{WSO}^{COV} = v - p + ksy - t$, respectively. The consumers will only make the purchase when their utilities are nonnegative. The consumers are store type when $U_{PPS}^{COV} \geq U_{WSO}^{COV}$, and they are WSO type otherwise. We hence get those consumers with $t \leq \xi$ are WSO type, i.e., $\theta^{EC} \equiv \min\{\frac{\xi}{\hat{t}}, 1\}$, while the remaining $(1-\theta^{EC})$ are store type. Note that, when $\xi \geq \hat{t}$, all consumers will be WSO type; when $\xi < \hat{t}$, we summarize consumer decisions as below:

$$\begin{cases} buy\ from\ physical\ store & if\ v > p - ksy + \xi\ and\ t > \xi; \\ buy\ from\ WSO & if\ v > p - ksy + t\ and\ t \leq \xi; \\ buy\ nothing & otherwise. \end{cases}$$

We use the superscript "EC" to demonstrate the scenario of endogenous consumer types, and have the following two cases:

(a) **Case I**: If $\xi \geq \hat{t}$, then $\theta^{EC} = 1$. We have $D_{WSO-I}^{EC} = 1 - p + lsy - \varphi$, where $\varphi = E(t) = \frac{\hat{t}}{2}$. The firm's profit is $\pi_{WSO-I}^{EC}(p,y) = (p-c-\beta-g)(1-p+ksy-\varphi) - \lambda s^2y^2 - fy$. Consumer surplus is $CS_{WSO-I}^{EC} = \int_{p-ksy+\varphi}^{1}(v-p+ksy-\varphi)\psi(v)\,dv = \frac{(1-p+ksy-\frac{\hat{t}}{2})^2}{2}$. Workers' welfare is $WW_{WSO-I}^{EC} = fy + \beta D_{WSO-I}^{EC}$. WCC welfare is $WCC_{WSO-I}^{EC} = \pi_{WSO-I}^{EC} + CS_{WSO-I}^{EC} + WW_{WSO-I}^{EC}$.

(b) **Case II**: If $\xi < \hat{t}$, we have $D_{WSO-II}^{EC} = \left(1-\frac{\xi}{\hat{t}}\right)(1-p+ksy-\xi) + \frac{\xi}{\hat{t}}(1-p+ksy-\varphi)$. The firm's profit is $\pi_{WSO-II}^{EC}(p,y) = (p-c-\beta)\left(1-\frac{\xi}{\hat{t}}\right)(1-p+ksy-\xi) + (p-c-\beta-g)\frac{\xi}{\hat{t}}(1-p+ksy-\varphi) - \lambda s^2y^2 - fy$. Consumer surplus is $CS_{WSO-II}^{EC} = \left(1-\frac{\xi}{\hat{t}}\right)\int_{p-ksy+\xi}^{1}(v-p+ksy-\xi)\psi(v)\,dv + \frac{\xi}{\hat{t}}\int_{p-ksy+t}^{1}(v-p+ksy-\varphi)\psi(v)\,dv = \frac{(1-\frac{\xi}{\hat{t}})(1-p+ksy-\xi)^2}{2} + \frac{\frac{\xi}{\hat{t}}(1-p+ksy-\frac{\hat{t}}{2})^2}{2}$. Workers' welfare is $WW_{WSO-II}^{EC} = fy + \beta D_{WSO-II}^{EC}$. WCC welfare is $WCC_{WSO-II}^{EC} = \pi_{WSO-II}^{EC} + CS_{WSO-II}^{EC} + WW_{WSO-II}^{EC}$.

Recall that we suppose $\lambda > \frac{k^2}{4}$. By finding the optimal decisions for each case, we yield Lemma 3.4.

Lemma 3.4. *(i) The firm's optimal retail price and employment level are:*

$$p_{WSO}^{EC*} = \begin{cases} \frac{s\lambda[2(1+c+g+\beta)-\hat{t}]-k[f+ks(c+g+\beta)]}{s(4\lambda-k^2)} & if \xi \geq \hat{t} \\ \frac{s\lambda[2\hat{t}(1+c+\beta)-3\hat{t}\xi+2\xi(g+\xi)]-k[f\hat{t}+k(s\hat{t}(c+\beta)+gs\xi)]}{s\hat{t}(4\lambda-k^2)} & if \xi < \hat{t} \end{cases} \textit{ and,}$$

$$y_{WSO}^{EC*} = \begin{cases} \frac{ks[2(1-c-g-\beta)-\hat{t}]-4f}{2s^2(4\lambda-k^2)} & if \xi \geq \hat{t} \\ \frac{ks[2\hat{t}(1-c-\beta)-3\hat{t}\xi-2\xi(g-\xi)]-4f\hat{t}}{2s^2\hat{t}(4\lambda-k^2)} & if \xi < \hat{t} \end{cases}, \textit{ respectively.}$$

(ii) $D_{WSO}^{EC*} \geq 0$ *if and only if* $\beta \leq \beta_{WSO}^{EC}$, *where* $\beta_{WSO}^{EC} = \begin{cases} 1-c-g-\frac{fk}{2s\lambda}-\frac{\hat{t}}{2} & if \xi \geq \hat{t} \\ 1-c-\frac{fk}{2s\lambda}-\frac{(2g+3\hat{t}-2\xi)\xi}{2\hat{t}} & if \xi < \hat{t} \end{cases}$.

(iii) $\beta_{WSO}^{EC} \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} \beta_{PPS}^{COV}$ if and only if $\xi \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} g + \frac{\hat{t}}{2}$.

The results derived in Lemma 3.4 are similar to the ones in the basic model (i.e., Lemma 3.3): (i) There exists a threshold for the maximum piece-rate wage, exceed which there will be no business for the firm. (ii) Implementing WSO cannot always help the firm to survive COVID-19 pandemic, especially when the consumers' fear of infection is relatively low. Next, we proceed to investigate the value of WSO implementation under the case of endogenous consumer types.

Proposition 3.6.

(i) $p_{WSO}^{EC*} > p_{PPS}^{COV*}$ and $y_{WSO}^{EC*} > y_{PPS}^{COV*}$ if and only if ξ is relatively large. (ii) $\pi_{WSO}^{EC*} > \pi_{PPS}^{COV*}$ if and only if $\begin{cases} \max\{1-c-\beta-\frac{fk}{2s\lambda}, \hat{t}\} < \xi < \frac{1}{2}(2g+\hat{t}) & \text{if } \xi \geq \hat{t} \\ 0 < \xi < \min\{\underline{\xi}, \hat{t}\} \text{ or } \bar{\xi} < \xi < \hat{t} & \text{if } \xi < \hat{t} \end{cases}$, otherwise, $\pi_{WSO}^{EC*} \leq \pi_{PPS}^{COV*}$, where $\underline{\xi}$ and $\bar{\xi}$ are the two positive roots of $Y^{EC}(\xi) = 0$. (iii) $WCC_{WSO}^{EC*} > WCC_{PPS}^{COV*}$ if and only if $\begin{cases} \max\{\underline{\xi}^{I}, \hat{t}\} < \xi < \bar{\xi}^{I} & \text{if } \xi \geq \hat{t} \\ \max\{\underline{\xi}^{II}, 0\} < \xi < \min\{\bar{\xi}^{II}, \hat{t}\} & \text{if } \xi < \hat{t} \text{ and } \lambda > \frac{(3+\sqrt{5})k^2}{4} \\ 0 < \xi < \min\{\underline{\xi}^{II}, \hat{t}\} \text{ or } \bar{\xi}^{II} < \xi < \hat{t} & \text{if } \xi < \hat{t} \text{ and } \lambda \leq \frac{(3+\sqrt{5})k^2}{4} \end{cases}$, otherwise, $WCC_{WSO}^{EC-COV*} \leq WCC_{PPS}^{COV*}$, where $Y^{EC}(\xi)$, $\underline{\xi}^{I}$, $\bar{\xi}^{I}$, $\underline{\xi}^{II}$ and $\bar{\xi}^{II}$ can be checked in Appendix B.

Proposition 3.6 obtains similar findings shown in the basic model, which proves the robustness of our research. First, the firm should employ more salespeople to sell higher-price products for WSO if the consumers' fear of infection under COVID-19 is relatively large; otherwise, the firm should cut down the price and dismiss salespeople. Second, when the consumers' fear of infection is moderate, WSO is likely to help improve the firm's profit and WCC welfare simultaneously. While particularly, we notice that when consumers can endogenously decide their types by themselves, it can be more recommended for the firm to adopt WSO. Concretely speaking, even when the consumers' fear of infection is extremely low (i.e., $0 < \xi < \min\{\underline{\xi}, \underline{\xi}^{II}, \hat{t}\}$), the firm still has an opportunity to achieve the PWI outcome as long as the service improvement cost coefficient is relatively low. This is because the extremely low fear of infection results in higher demand in the physical store, which helps the firm to save a huge amount of delivery cost; consequently, the firm can have opportunities to achieve the PWI outcome in this scenario.

3.5.2 Endogenous Service Level

In this subchapter, we further consider the case when the service level (s) is endogenously determined. Since sales service plays a key role that affects the firm's optimal operations strategy, especially for WSO, making a wise service level decision is meaningful for this research. We use the superscript "ES" to denote this case. In this case, we consider that the service level improvement cost should not be over a value H, that is $IC(T) \leq H$. Note that, this constraint is considered to ensure that the optimal unit service level s can be obtained in this case. There is no need to consider it in basic model as the unit service level is exogenously given. It represents that the firm total investment in service is limited with a fixed value and this setting fits the real-world industrial observations and is supported by prior studies in the literature. For example, there always exists a budget constraint on improving sales force (Murthy and Mantrala, 2005). A Harvard Business Review article also highlights this consideration through investigating industrial practices (Chung, 2015). Therefore, it is important to take the constraint of service level into consideration when the firm makes manpower decisions. In other words, the firm should first decide the unit service level s endogenously under the budget constraint, and then set the price p and employment level y accordingly, aiming at optimizing its total profit. By using the same methods as the ones in the basic model, we derive Lemma 3.5. All the optimal decisions are shown in Table A3-1 in Appendix B.

Lemma 3.5. *(i) In all three models (i.e., PPS, PPS-C, and WSO), the firm will set its unit service level* s *at the maximum value, i.e.,* $\frac{\partial \pi_i^{ES}(p(s),y(s))}{\partial s} \geq 0$. *(ii)* $D_{PPS}^{ES-COV*} \geq 0$ *if and only if* $\beta \leq \beta_{PPS}^{ES-\overline{COV}} \leq \beta_{PPS}^{ES-COV}$, *where* $\beta_{PPS}^{ES-\overline{COV}} = 1 - c + \frac{\sqrt{2}Hk}{\sqrt{H\lambda}}$ *and* $\beta_{PPS}^{ES-COV} = 1 - c + \frac{\sqrt{2}Hk}{\sqrt{H\lambda}} - \xi$. *(iii)* $\beta_{WSO}^{ES} \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} \beta_{PPS}^{ES-COV}$ *if and only if* $\xi \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} g + t$ *where* $\beta_{WSO}^{ES} = \frac{\sqrt{2}k\sqrt{H\lambda} - \lambda(-1+c+\theta(g+t-\xi)+\xi)}{\lambda}$.

Observing the results in Lemma 3.5, it is straightforward to notice that there is a maximum piece-rate wage to make sure that the firm has businesses. Thresholds of piece-rate wage have the same relations as the basic model. Besides, to be noticed that it is always beneficial for the firm to set the unit service level as the maximum value since the improvement of service level induces the increase of marginal benefit that the firm can obtain. Next, we show that the impacts of COVID-19 and the values of WSO mode keep the same when the firm endogenously decides the optimal unit service level.

Proposition 3.7. *(i)* $p_{PPS}^{ES-COV*} < p_{PPS}^{ES-\overline{COV}*}$, $y_{PPS}^{ES-COV*} < y_{PPS}^{ES-\overline{COV}*}$, *and* $s_{PPS}^{ES-COV*} > s_{PPS}^{ES-\overline{COV}*}$*; (ii)* $\pi_{PPS}^{ES-COV*} < \pi_{PPS}^{ES-\overline{COV}*}$ *;* $WCC_{PPS}^{ES-COV*} < WCC_{PPS}^{ES-\overline{COV}*}$.

Proposition 3.7(i) verifies that the existence of COVID-19 leads to a price reduction and lowers the employment level. What needs to pay attention to is that COVID-19 enhances the requirement of unit service level provided by each salesperson. In other words, the optimal unit service level under COVID-19 is higher than that without the pandemic. It is because the lower employment level puts stress on salespeople and requires a higher unit service level to ensure the demand. Proposition 3.7(ii) highlights that COVID-19 pandemic seriously hit the operations of physical stores, not only decreasing the profit but also the WCC welfare, even though the firm endogenously decides the optimal unit service level. Proposition 3.7 demonstrates that our findings on the impacts of COVID-19 are still valid when unit service levels are endogenously given. We then seek the values of WSO implementation.

Proposition 3.8 *(i)* $p_{WSO}^{ES*} > p_{PPS}^{ES-COV*}$, $y_{WSO}^{ES*} > y_{PPS}^{ES-COV*}$, *and* $s_{SO}^{ES*} < s_{PPS}^{ES-COV*}$ *if and only if* ξ *is relatively large; (ii)* $\pi_{WSO}^{ES*} > \pi_{PPS}^{ES-COV*}$ *if and only if* $\theta > \theta'^{ES}$, *otherwise* $\pi_{WSO}^{ES*} \leq \pi_{PPS}^{ES-COV*}$ *where* $\theta'^{ES} = -\frac{2(g(-1+c+2t+\beta-\xi)+(t-\xi)(-1+c+\beta+\xi))}{(g-t+\xi)^2}$*; (iii)* $WCC_{WSO}^{ES*} > WCC_{PPS}^{ES-COV*}$ *if and only if* $\xi \in (\underline{\xi^{ES}}, \overline{\xi^{ES}})$ *where* $\underline{\xi^{ES}} = \max\{0, min\{root_1, root_2\}\}$ *and* $\overline{\xi^{ES}} = \max\{root_1, root_2\}$ *are two positive roots of* $X^{ES}(\xi)$*, where* $X^{ES}(\xi)$ *can be checked in Appendix B; otherwise,* $WCC_{SO}^{ES*} \leq WCC_{PPS}^{ES-COV*}$.

We can observe from Proposition 3.8(i) that the consumers' fear of infection plays the same role in affecting the firm's optimal pricing and employment level as the basic model. That is, relatively large fear of infection induces higher retail price and stimulate the firm hires more salespeople after implementing WSO. While the unit service level of salesperson may not be strictly required because more salespeople will be hired when WSO is implemented, and the total service level can be satisfied by the high level of employment. Second, Proposition 3.8(ii) demonstrates the value of WSO implementation depends on the consumer type distribution. Similar to the basic model, only when the proportion of WSO consumers is relatively large, the firm can earn profits and achieve a higher WCC welfare from the implementation of WSO.

3.5.3 WCC-welfare-oriented Firm

Under COVID-19, unemployment is a critical issue worthy of attention. Our analytical results in Proposition 3.2(i) also have shown that the employment level of salesperson will be reduced by COVID-19. This unemployment will definitely harm workers' welfare, which is unexpected. Hence, during this special period of pandemic, economic objectives of the firm may have to change to optimize WCC welfare. We call this kind of firm as WWC-welfare-oriented firm (denoted by the superscript "WO"). For the WCC-welfare-oriented firm, the retail price and the employment level are determined to maximize the firm's WCC welfare $WCC = \alpha\pi + \omega(CS + WW)$, where $\alpha(> 0)$ and $\omega(> 0)$ denote the weight of profit and social responsibilities in WCC welfare, respectively (Benjaafar et al., 2019). For simplicity, we normalize ω to 1; hence, $\alpha > 1$ implies that the firm focuses more on its own profit than consumer and workers' welfare, and vice versa. The optimal decisions for the WWC-welfare-oriented firm can be checked in Table A3-2 in Appendix B.

Proposition 3.9. *WCC-welfare-oriented firm is less likely to lose all the business (i.e., $D^* = 0$) than profit-oriented firm.*

Proposition 3.9 provides an interesting finding that the WCC-welfare-oriented firm could be superior to the profit-oriented firm in terms of keeping business (i.e., having positive demand). According to our common knowledge, the WCC-welfare-oriented firm seems much easier to lose its business as it put more emphasis on consumer and workers' welfare rather than its own profit; however, its efforts on maximizing total WCC welfare exactly gives itself an opportunity to attract more consumers, which eventually gains a higher market demand. We hence strongly suggest the firm to concentrate more attention on total WCC welfare when making decisions, which can not only benefit its own business but also be conducive to the whole society.

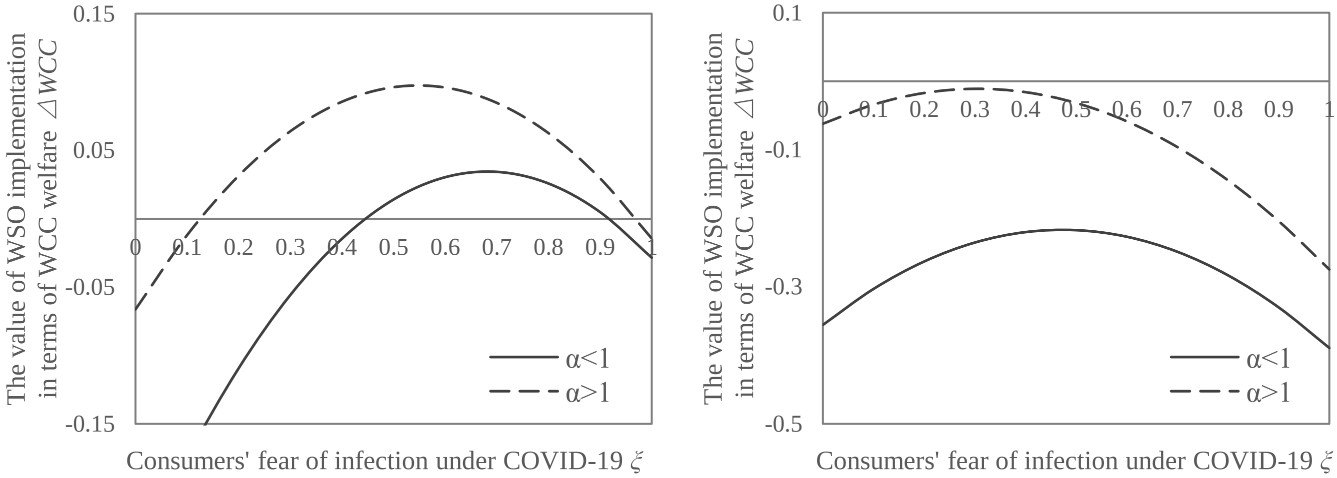
Next, we proceed to explore the impacts of COVID-19 and values of WSO implementation for the WCC-welfare-oriented firm. Due to the complexity, we will first derive analytical results for the special case in which $\alpha = 1$ in Proposition 3.10, and then conduct numerical studies to examine general cases where $\alpha < 1$ and $\alpha > 1$ in Figure 3-2.

Proposition 3.10 (special case in which $\boldsymbol{\alpha = 1}$). *(i) $\pi_{PPS}^{WO-COV*} > \pi_{PPS}^{WO-\overline{COV}*}$ and $WCC_{PPS}^{WO-COV*} < WCC_{PPS}^{WO-\overline{COV}*}$. (ii) $\pi_{WSO}^{WO*} > \pi_{PPS}^{WO-COV*}$ if and only if $0 < \xi < \underline{\xi}^X$ or $\xi > \overline{\xi}^X$, otherwise, $\pi_{WSO}^{WO*} \leq$*

$\pi_{PPS}^{WO-COV*}$, *where* $\underline{\xi}^X$ *and* $\overline{\xi}^X$ *are the two positive roots of equation* $Y(\xi)^{WO} = -k^2 s(2-\theta)\lambda\xi^2 + (f(2k\lambda - k^3) + s(2k^2(1-c-\beta+t(1-\theta))\lambda + 4\beta\lambda^2 + g(1-\theta)(k^4 - 2k^2\lambda + 4\lambda^2)))\xi + fk(g+t)(k^2-2\lambda) - s(gk^4 t(1-\theta) + k^2(2(t+g)(1-c-\beta) - 4gt - (g-t)^2\theta)\lambda + 4(t\beta + g(t+\beta-t\theta))\lambda^2)$. *(iii) There exists a threshold* c^T. *When* $c \geq c^T$, *we have* $WCC_{WSO}^{WO*} \leq SW_{PPS}^{WO-COV*}$; *while when* $c < c^T$, $WCC_{WSO}^{WO*} > WCC_{PPS}^{WO-COV*}$ *if and only if* $max\left\{0, \underline{\xi}^Y\right\} < \xi < \overline{\xi}^Y$, *otherwise,* $WCC_{WSO}^{WO*} \leq WCC_{PPS}^{WO-COV*}$, *where* $\underline{\xi}^Y$ *and* $\overline{\xi}^Y$ *are the two positive roots of equation* $X(\xi)^{WO} = -(k^2(1-\theta) + 2\lambda)\xi^2 + (2k^2(g+t)(1-\theta) + 4(1-c)\lambda)\xi - k^2 t(2g+t)(1-\theta) + 2(-2g(1-c-t) - t(2-2c-t) + g^2\theta)\lambda$.

Proposition 3.10(i) shows the impacts of COVID-19 on the WCC-welfare-oriented firm's performance. The same with the basic model, we find that COVID-19 is always detrimental to the firm in terms of WCC welfare; while we surprisingly notice that the WCC-welfare-oriented firm can earn more profit with COVID-19 pandemic than without. The reason behind is that the outbreak of COVID-19 damages consumer surplus due to the fear of infection, hence the WCC-welfare-oriented firm has to make great efforts on earning more profit so as to make up for the loss in consumer surplus and achieve its optimal WCC welfare. Propositions 3.10(ii) and (iii) present the values of implementing WSO under COVID-19. The results reveal that the production cost should be an important factor for the WCC-welfare-oriented firm. Specifically, when the production cost is relatively large, implementing WSO can never benefit the firm's WCC welfare; and when the production cost is relatively small, the firm can achieve a higher WCC welfare when the consumers' fear of infection is moderate. Thus, we kindly remind those WCC-welfare-oriented firms with a high production cost to avoid implementing WSO under COVID-19, as it will harm the WCC welfare.

Next, we focus on investigating general cases where $\alpha \neq 1$. We define $\Delta WCC = WCC_{WSO}^{WO*} - SW_{PPS}^{WO-COV*}$ as the value of WSO implementation in terms of WCC welfare. The positive ΔWCC means that the firm can gain a higher WCC welfare when implementing WSO, and vice versa. Figure 3-2 is depicted for both cases where $\alpha > 1$ and $\alpha < 1$.



(a) When $c < c^T$ (b) When $c \geq c^T$

Figure 4-2. The value of WSO implementation in terms of WCC welfare in general cases (We let $\beta = 0.3$, $\lambda = 0.2$, $k = 0.25$, $s = 0.6$, $f = 0.05$, $t = 0.05$, $g = 0.1$, $\alpha = 0.8$ or 1.2, and $c = 0.3$ in (a), $c = 0.5$ in (b)).

Figure 3-2 demonstrates the value of WSO implementation with respect to WCC welfare. As we can observe, in general cases where $\alpha \neq 1$, the findings obtained in Proposition 3.10 still hold: (i) the WCC-welfare-oriented firm with high production cost (i.e., Figure 3-2(b)) always achieve a lower WCC welfare under the implementation of WSO; (ii) the WCC-welfare-oriented firm with high production cost (i.e., Figure 3-2(a)) can benefit from WSO implementation if the consumers' fear of infection is moderate, irrespective to the firm's attitude towards WCC welfare, i.e., $\alpha > 1$ and $\alpha < 1$. Besides, we notice that WSO implementation tends to be more valuable for the firm that pays more attention to its profit in WCC welfare (i.e., $\alpha > 1$) than the firm that treasures consumer and workers' welfare more in WCC welfare (i.e., $\alpha < 1$). This is because the main value of WSO is to stimulate additional demand for the firm, which makes great contributions to increasing total profit rather than consumer and workers' welfare. Hence, we can easily understand that why the firm focusing more on profit is more likely to benefit from WSO implementation.

3.6 Summary

3.6.1 Concluding Remarks

Motivated by the interesting real-world observation of Timberland case, we conduct an interview with the salespeople of Timberland in Hong Kong, and then based on the primary data collected through the interview, we establish an innovative theoretical model to explore WSO. By proposing a standard consumer utility-based model, we capture the consumer's purchasing behavior with regard to the retail price, total service level, their fear of infection under COVID-19, and their potential concerns for WSO. We evaluate the firm's optimal pricing and employment decisions under three possible cases: (i) without COVID-19 and the firm operates a pure physical store (Model PPS), (ii) with COVID-19 and the firm operates a pure physical store (Model PPS-C), and (iii) with COVID-19 and the firm operates WSO (Model WSO). In each case, we explore the firm's optimal profit, consumer surplus, and workers' welfare; and integrated them into a novel concept of Worker-Consumer-Company (WCC) welfare, which is used to reflect the welfare performance with the special consideration of workers' welfare. We regard WCC welfare as a critically important indicator that should be considered, as it reflects the influence of COVID-19 on the whole society, rather than on the firm solely. By comparing the three cases, we successfully identify the impacts of COVID-19 pandemic on physical store operations as well as the values of WSO implementation under pandemic in terms of both firm's profit and WCC welfare. Moreover, we further extend our model by considering scenarios with the endogenous consumer type, endogenous service level, and the WCC-welfare-oriented firm to check the robustness of our study.

3.6.2 Managerial Implications

To our best knowledge, this is the first study examining WSO under COVID-19. The obtained insights not only contribute to the literature, but also provide practical guidance to operations managers for the potential applications and values of WSO. We summarize the important managerial implications to the firm from the following three aspects: (i) impacts of COVID-19, (ii) values of WSO, and (iii) guidance on the improvement of WSO performance.

Impacts of COVID-19: Our analytical results verify that COVID-19 will inevitably damage the firm's physical store operations. It is hence important for retail firms to change their operations pattern (e.g., implementing WSO) to seek survivals. Despite that the pandemic was over, the consumer's change of behavior is long-lasting (PwC 2020), which requires the firms to adapt to the new normal by considering the use of WSO.

Values of WSO: (ii) The implementation of WSO is able to stimulate demand in the physical store under COVID-19 when consumers have a higher fear of infection. This finding shows the significance of implementing WSO as it can help eliminate the demand reduction in the physical store channel caused by COVID-19 so as to enhance the resilience ability of the firm. (ii) Nevertheless, the implementation of WSO is not always recommended for the firm under COVID-19; whether it is valuable to adopt WSO depends on both consumers' fear of infection and consumer type distribution. We summarize the managerial insights of WSO implementation in Figure 3-3 and Table 3-4, which provide an overview of the firm's optimal operation strategy.

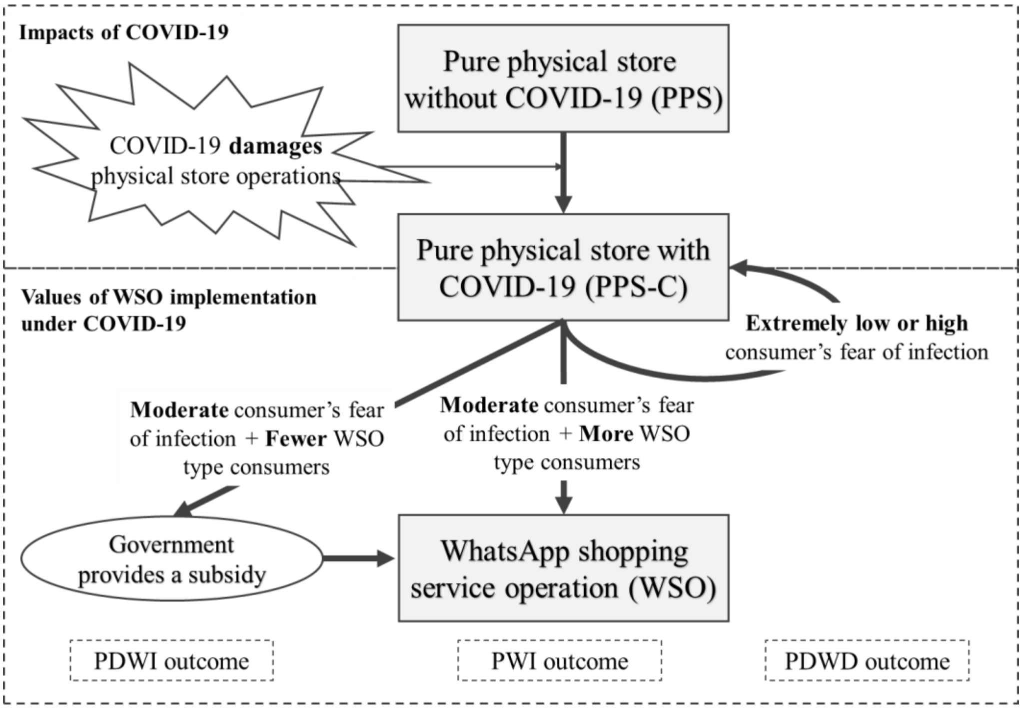


Figure 5-3. Shifts in the firm's optimal operations strategy under different conditions.
(Remarks: PWI means "profit-welfare-improvement", PDWI means "profit-decreasing welfare-increasing", and PDWD means "profit-decreasing welfare-decreasing")

Table 4-4. Summary of the firm's optimal operations strategy under COVID-19.

		Consumers' fear of infection		
		High	Moderate	Low
Proportion of WSO type consumers	High	**Pure physical store**	**WhatsApp shopping service operation (WSO)**	**Pure physical store**
	Low		**WSO with government's subsidy**	

As shown in Figure 3-3 and Table 3-4, we suggest that when the consumers' fear of infection is very polarized, (i.e., extremely low or high), WSO should not be recommended as it is harmful to both the firm's profit and WCC welfare (i.e., the PDWD outcome); in this case, the firm should still operate a pure physical store (Model PPS-C) under the COVID-19 pandemic. This counter-intuitive finding is due to the price hike of WSO under the high fear of infection case (see Proposition 3.4(i)), which eventually cuts the demand as well as harms the firm's WCC welfare. When the consumers' fear of infection is moderate, the firm can shift to Model WSO without hesitation if there are more WSO type consumers in the market, as the profit-welfare-improvement (PWI) outcome can be achieved; while if there are fewer WSO type consumers in the market (e.g., for the product requiring strong experience such as automobile), the PDWI (profit-decreasing welfare-increasing) outcome can be achieved, we hence suggest the government conduct an incentive mechanism (e.g., providing a subsidy) for the firm's WSO implementation, which is an effective way to help firm survive COVID-19 as well as improve WCC welfare.

Guidance on the improvement of WSO performance: (i) We find that the firm with a lower service improvement cost coefficient could have a higher incentive to implement WSO. It is the reason why not all stores of a brand would like to provide WSO in practice. (ii) The firm should take measures to enlarge the number of WSO type consumers, e.g., by advertising more about WSO mode, so as to boost its total profit. This is the case in Timberland (HK) as the brand advertised hard on social media platforms such as Facebook during the time when COIVD-19 pandemic was very serious. (iii) We find that the WCC-welfare-oriented firm is superior to the profit-oriented firm in terms of keeping business (i.e., having positive demand). It is important to note that the implementation of WSO is not helpful to improve WCC welfare when the production cost of the WCC-welfare-oriented firm is relatively high. We hence recommend the WCC-welfare-oriented firm with a high production cost to adopt the pure physical store operational mode under COVID-19.

Chapter 4 Government Subsidies and Policies for Mask Production under COVID-19[8,9]

The review findings in Chapter 2 uncover that the government's incentive mechanism can potentially increase demand under the pandemic to achieve supply chain resilience, which is worthy of deep investigation. Paying attention to the production issues faced by supply chains under the pandemic, Chapter 4 examines the role of government's subsidies and policies in mask production, aiming to provide guidance to both the government and mask manufacturer in combating COVID-19.

4.1 Problem Description

4.1.1 Research Background

Since December 2019, the coronavirus (COVID-19) pandemic has quickly become a global public healthcare crisis (Kaplan 2020). Proper prevention and control are important (Li et al. 2022) when curbing highly infectious diseases such as COVID-19 (Adida et al. 2013; Choudhary et al. 2021). According to the most up-to-date recommendations of the World Health Organization (WHO 2020), diseases like COVID-19 and SARS can be reduced and controlled with the use of facial masks. At present, most countries urge citizens to wear masks during the outbreak of COVID-19. Under the threat of pandemics such as COVID-19, on the one hand, encouraging citizens to wear masks is important; on the other hand, developing an efficient mask supply chain (MSC) plays a critical role. However, owing to the high production uncertainty and cost for the healthcare system (Demirezen et al. 2016), the performance and resilience of the critical item supply chains, such as MSCs, are being challenged (Sodhi et al. 2021), which requires the public's efforts to overcome.

According to the public interest theory, government's regulation and control are helpful to conquer the unbalanced supply chain operations and undesirable market results, which can be an efficient way to maximize social welfare (Bozeman, 2007). In real-world practices, governments have

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[8] A part of this chapter has been published in: "Xu, X., Choi, T.M., Chung, S.H., Shen, B. (2022). Government subsidies and policies for mask production under COVID-19: Is it wise to control less? IEEE Transactions on Engineering Management, published online: 10.1109/TEM.2022.3198101." and "Xu, X., Chung, S.H., Lo, C.K., Yeung, A.C. (2022). Sustainable supply chain management with NGOs, NPOs, and charity organizations: A systematic review and research agenda. Transportation Research Part E: Logistics and Transportation Review, 164, 102822."

[9] The notations used in this chapter are self-contained and only valid for this chapter.

launched different subsidy programs (consumer and manufacturer subsidies) to not only induce local manufacturing for enhancing supply, but also encourage consumers to buy and use masks during the COVID-19 outbreak. For instance, Hong Kong, Japan, Germany, and Italy announced in 2020 that they would subsidize manufacturers for mask production, that is, adopting the manufacturer subsidy scheme, whereas Mainland China and Singapore subsidized consumers directly when purchasing masks, that is, implementing the consumer subsidy scheme. We summarize governments' subsidy programs for MSCs during the COVID-19 outbreak in Table A4-1 in Appendix A. In academia, prior studies have proved the efficiency of subsidy program in improving social welfare (Xu et al. 2022b) and indicated that the optimal subsidy program is decided on the basis of the pricing and the government's attitude toward social welfare (Yu et al. 2018). Undoubtedly, both manufacturer and consumer subsidies can help enhance manufacturers' benefits (Berenguer et al. 2017). However, the question of under what condition, which subsidy program is more preferable for the government to tackle a pandemic like COVID-19 is unclear.

Nevertheless, the subsidy programs during the pandemic can be supported by the public interest theory which refers to the government aims at benefiting the whole society but usually neglects the particular vested interests (Deegan and Unerman, 2011). From the manufacturer's perspective, due to yield problem, a manufacturer may over-claim its production yield to gain an extra subsidy. This dishonest behavior may lead to a loss to the society. To combat dishonest behaviors, the government need to explore solutions. For instance, in Hong Kong, the government requires the manufacturers which apply for subsidies to submit evidence of their production capacity and conducts on-site monitoring for those approved production lines (Hong Kong Productivity Council 2020). This way of monitoring is not only costly, but also inefficient to eliminate data fraud. Hence, it is necessary to find out a more efficient way for the government to prevent dishonesty, e.g., by implementing technologies such as blockchain to ensure the honesty of manufacturers and lessen the risk of dishonest problems (Babich and Hilary 2020, p. 12). From the consumer's perspective, mask price control policy is proposed to maintain or improve the consumer's benefit. Many governments have imposed different levels of pricing control on masks to avoid speculation and ensure consumer affordability (Rotondi 2020). For example, in April 2020, the Italian government introduced the policy in which the unit price of a mask cannot be higher than €0.5. In Mainland China, the State Administration for Market Regulation announced that the price of masks during the pandemic must be maintained at the same level as the one before the pandemic. In this study, we analytically compare different subsidy schemes as well as explore the impacts of control policies (preventing dishonesty, price control) on MSCs in the related models, which are underexplored in the prior literature.

This research on government subsidies in an MSC is most related to two research domains: (i) healthcare challenges in OM, and (ii) government sponsor/subsidy. In healthcare OM, some prior studies provide important insights to enhance operations performances of healthcare organizations and hospitals (e.g., Wong et al. 2014, Kuo et al. 2016, Perera and Dabney 2020), some of them investigate pharmaceutical supply chain operations (e.g., Zhao et al. 2012, Taylor and Xiao 2014, Olsder et al. 2022), and some of them focus on vaccine supply chain management (e.g., Chick et al. 2008, Arifoğlu et al. 2012, Dai 2015, Arifoğlu and Tang 2022). In this study, we follow Kaplan (2020)'s transmission model to capture the social health risk brought by the COVID-19 outbreak and integrate it into our own theoretical model analyses. Then, subsidy design is important in various industries, such as medicine (Taylor and Xiao 2014), technology (Cohen et al. 2016), and agriculture (Alizamir et al. 2018). Among them, healthcare related subsidy is most related to this study, including Taylor and Xiao (2014), Qian et al. (2017), Olsder et al. (2022), Yu et al. (2018), etc. The prior literature has well explored the effectiveness of different subsidy schemes; however, the impacts of social health risk and government's control policies on subsidy design are unknown. We hence conduct this research to fill the gap.

4.1.2 Research Questions and Contribution

Based on the above background, we develop an analytical model integrating the government's subsidy decisions, manufacturer's production problems, and consumers' behaviors in an MSC. We consider two subsidy programs, namely, the consumer subsidy (Model C) and manufacturer subsidy (Model M), which have been implemented during the COVID-19 outbreak in different countries (see Table A4-1). As a remark, wearing masks is effective to curb the spread of diseases like SARS, H1N1 and COVID-19. Specifically, we attempt to address the following three key research questions (RQs):

RQ1: Focusing on the government, what is the more efficient subsidy scheme (consumer and manufacturer subsidies) under the COVID-19 pandemic?

RQ2: Focusing on the manufacturer, how the manufacturer's dishonest behavior affects the government's supervisory strategy (e.g., the use of blockchain)?

RQ3: Focusing on consumers, how does the price control policy affect consumer welfare during the outbreaks?

Addressing the above research questions generates various insights. First, the provision of subsidies is effective in preventing the spread of a virus and improving MSC performance. Consumer subsidy and manufacturer subsidy models (i.e., Models C and M, respectively) offer equal benefits for consumers and the manufacturer when the price is not controlled by the government. This result is consistent with the findings reported by Berenguer et al. (2017), but different from Taylor and Xiao (2014). In addition, distinct from prior studies, we notice that adopting the model with a lower subsidy implementation cost can lead to higher social welfare. This finding is critical because the governments must respond as quickly as possible during the COVID-19 outbreak, and the subsidy scheme which is easier to implement in practice should be adopted. All these findings continue to hold when there are multiple manufacturers in the MSC Second, we theoretically examine the value of dishonesty prevention policy on supply chain performance. The use of blockchain can eliminate the over-claiming problem of production quantity caused by subsidy provision. Surprisingly, the government may "turn a blind eye" to the dishonest behavior during the COVID-19 outbreak. This is because dishonesty does not harm supply chain performance if the dishonest behavior can be anticipated. Even if the dishonest behavior cannot be anticipated, the government who has adequate financial resources should still "turn a blind eye" to the dishonest behavior because it is helpful in the improvement of social welfare and health risk reduction during the COVID-19 outbreak. Using blockchain is helpful for the budget-limited government which is concerned about expenditures because blockchain is effective in preventing dishonesty and helps eliminate the corresponding negative effect on social welfare. However, using blockchain is not effective in increasing consumer surplus, which is caused by the implied quality reduction of masks. Third, we derive the counter-intuitive results that the price control policy is in fact harmful to consumers but may benefit the manufacturer if the controlled price is sufficiently high. This is because under the price control policy, the manufacturer may lower the mask quality level, which helps the manufacturer to save costs while sacrificing the consumers' benefit. The price control policy is recommended to improve social welfare if the infection rate is sufficiently high. The price control policy is hence particularly important during the early stage of the COVID-19 outbreak (i.e., when the infection rate is high). Note that under the price control policy, Models C and M are no longer equal in performance. In order to obtain the optimal social welfare, the controlled price set in Model C should be higher than that in Model M. When the controlled price is given at the same level, Model CG (i.e., Model C with a controlled price) is more profitable for the manufacturer if the infection rate is sufficiently low. In other words, the government's excessive intervention (e.g., dishonest prevention and price control) will cause the disequilibrium in the MSC.

To our best knowledge, this work is the first study to analytically evaluate the efficiency of government subsidy programs in an MSC under a disease outbreak such as COVID-19. We utilize the infection transmission model to capture the health risk performance in social welfare, which is a unique feature of COVID-19. We highlight the impacts of subsidies on social welfare, and the impacts of government's control during the pandemic. Consisting with the public interest theory and existing literature (e.g., Berenguer et al. 2017), our findings verify the efficiency of government's subsidy program in improving social welfare, while provide new implications on avoiding excessive intervention under the pandemic. The insights derived not only contribute to the OM literature by enriching the studies on government subsidies but also generate managerial insights for governments, manufacturers, and consumers regarding the proper use of subsidy programs to enhance social welfare and MSC performance during the COVID-19 outbreak.

4.2 MSC Characteristics: Interviews, Discussion and Analysis

4.2.1 Real-World MSCs

This work is motivated by the real-world challenges faced by MSCs under the COVID-19 pandemic as well as the real practices of government subsidies and policies. On this account, we attempt to get more real-world data to support our motivation before conducting the theoretical study. To be specific, We not only have collected the public industrial news (see Chapter 4.1.1 and Table A4-1 in Appendix A), but also received the industrial inputs through an interview with Foshan Nanhai Beautiful Nonwoven Co., Ltd, one of the largest Chinese mask manufacturers located in Guangdong Province. Through the interview, we have collected reliable primary data relevant to the MSC operations. The interview results help motivate this study, support the construction of theoretical models, enhance the industrial relevance in our discussions, and validate our major findings. This kind of pre-analysis interview is not unusual in OM literature (e.g., Iyer and Bergen 1997; Chandrasekaran et al. 2016). The use of multi-method approach (combining industrial interviews with analytical models) can help enhance research rigor and better connect findings with real-world practices (Sodhi and Tang, 2014). Hence this study is not only theoretical but also practical-driven with primary data and industrial inputs.

Specifically, we have conducted an open-ended interview with the CEO of Foshan Nanhai Beautiful Nonwoven Co., Ltd, named Weiqi Deng (P.S.: The interview guide and original data are provided in Appendix C). Through the open-ended interviews and discussions, we attempt to (i) identify the features of MSC under COVID-19, (ii) understand the subsidies and policies implemented by the government to MSCs, and (iii) explore the potential impacts of government's subsidies and policies on MSCs. We summarize the interview results in Table 4-1 as an overview.

Table 4-1. Summary of interview results.

Features of MSC under COVID-19	Advantages: - Huge demand in mainland China, Hong Kong, and Japan at the beginning of COVID-19. - Simple equipment and materials for single-use face and surgical masks with lower quality, while relatively complex equipment and materials for respirator masks (e.g., N95, N99, etc.) with higher quality.
	Challenges: - May face disruption risks during the pandemic if the firm does not have its own raw material production line. - Even if the firm has its own raw material production line, the cost of material production is higher than before.
	Decisions: - The firm makes pricing decisions carefully during the COVID-19 pandemic. - The firm sets different quality levels for different orders of masks.
Subsidies and policies implemented by the government to MSC	- The Chinese government provides the subsidies to MSCs, including subsidizing the mask production and warehouse construction. - The subsidy amount is reduced with the pandemic period; and the subsidy program is cancelled started from August 2020. - The Chinese government imposes the price control policy during the pandemic.
Impacts of government's subsidies and policies on MSC	- Increasing production capacity. - Proposing "Ten Million Mask Plan", which helps the MSC to match the increased demand during the pandemic.

4.2.2 MSC Characteristics

According to the industrial data collected from the interview and combining with real-world observations, we attempt to highlight critical characteristics of MSCs under the COVID-19 pandemic so that our analytical models can better reflect the reality. (i) **Supply disruption:** Disruption risks may emerge during the pandemic because of unexpected labor and resource shortage problems in the "Great Lockdown" (see Craighead et al. 2020, Cohen et al. 2022, Nagurney 2021, and interview results in Table 4-1). This is especially severe in MSCs because the demand of masks increased dramatically. Both Hong Kong and the United States have claimed to face a shortage of face masks as global demand surged with the increasing number of infections worldwide" (Gu 2020, Nierenberg 2020). (ii) **Timely risk prevention:** Since June 2020, WHO has formally advised people to use masks during the COVID-19 outbreak (WHO 2020) owing to masks' effective prevention of viral infection and the ability to lower potential health risks in society. This risk prevention is timely. Masks can be quickly and simply used for preventing all kinds of respiratory diseases. (iii) **Varying quality performance in terms of different types of masks**: Various types of masks are available, including the single-use face mask, surgical mask, respiration mask (quality performance: single-use face mask < surgical mask < respiration mask). Mask types with varying quality performance drive the effectiveness of preventing the spread of virus. Usually, a manufacturer differentiates its product with others through product quality (Koufteros and Mar, 2006), and it can decide the optimal type of masks with respect to the market situation and costs. (iv) **Control on production standards:** To enter the market, manufacturers must produce qualified masks that pass the production test and meet the basic production requirements (e.g., three layers, particle filtration efficiency of >95%). During the COVID-19 outbreak, mask production standards are provided by the government. For example, in Mainland China, the State Administration for Market Regulation is responsible for the production supervision of masks. In the United States, the American Society for Testing and Materials sets standard specifications for the performance of materials used in medical face masks. They may adjust the quality standard in terms of the situation of COVID-19 spread. Note that, we want to clarify the significance of exploring the MSCs rather than other healthcare products under the pandemic, which are two-fold: (i) The MSCs mainly focuses on the problems of production (e.g., supply disruption, quality control), which is different from the vaccine supply chains that face the service operations problems. (ii) The use of masks works for the prevention of infection, while the drugs work the recovery after infection; they hence play totally different roles during the pandemic.

4.3 Basic Model

In the basic model, we consider an MSC consisting of a government, a mask manufacturer, and consumers. The government can grant a subsidy *s* to consumers (Model C) or the manufacturer (Model M). In Model C, a unit subsidy is provided to the consumers who purchase the mask; in Model M, a unit subsidy is granted to the mask manufacturer to partially cover its production cost. The settings are consistent with the mainstream OM papers (e.g., Berenguer et al. 2017; Yu et al. 2018; Yu et al. 2020). As a remark, the case where the government grants subsidies to both recipients is not explored here for two reasons: (i) the two subsidies are less commonly offered simultaneously in observed real-world practices (refer to Table A4-1 in Appendix A) and (ii) considering the two subsidy programs together makes no difference compared with the single case. The manufacturer produces masks that can prevent virus in terms of the rate of filtering airborne particles $q \in [0,1)$ (e.g., N99 can filter at least 99% of airborne particles, and N95 can filter at least 95% of airborne particles, etc.). The rate of filtering airborne particles is regarded as the mask's quality performance in this paper. As we mentioned in research background and interview results, quality performance refers to the effectiveness of preventing the spread of virus, which can be controlled by the manufacturer, e.g., using different equipment, materials, and number of layers. The government's fixed implementation cost of the subsidy is F_i, where $i = C$ or M. In practice, implementing subsidy programs incurs a non-trivial cost. In Model C, the fixed cost refers to the cost of arranging information systems under which consumers who purchase can redeem directly from the seller. In Model M, the fixed cost refers to the paper work and monitoring cost. The game sequence is as follows. First, the government decides the subsidizing target (Model C or M) and the corresponding amount of subsidy. Second, the manufacturer sets the price *p* and quality level q simultaneously. Third, consumers make their purchasing decisions. The framework of basic model can be found in Figure A4-1 in Appendix A.

4.3.1 Consumers' Problem

For notational purposes, we denote "buying" and "not buying" by subscripts *b* and *nb*, respectively. We define $\delta_b(q) = \tau(1-q)$ and $\delta_{nb} = \tau$ as the infection probabilities for individuals who buy and do not buy masks, respectively, where τ is the "original infection rate" associated with the virus. Here, please notice the difference between the concepts of "infection probabilities" and "original infection rate". The "infection probabilities" (δ_b and δ_{nb}) refer to the possibilities that the individuals will be infected by the virus after deciding to use or not to use the mask, which depend on both the "original infection rate" of the virus (τ) and the quality of the mask (q). We explain the rationale of this setting as follows: (i) The use of masks can help prevent viral infection. This important setting can be supported by the prior studies (e.g., Cheng et al. 2020, Howard et al. 2021), which have proven that the use of mask is the most effective way to reduce spread of the virus. The effectiveness relates to mask quality, that is, δ_b is a decreasing function in the quality level of masks. (ii) Without the viral outbreak, the infection probability is nonexistent regardless of using a mask or not, that is, $\delta_b \mid (\tau = 0) = \delta_{nb} \mid (\tau = 0) = 0$. (iii) When the quality of the mask is poor ($q = 0$), the mask is totally useless (i.e., the infection probability of using a mask will be the same as that of not using one, $\delta_b(0) = \delta_{nb}(0) = \tau$). The above features well capture the case with the COVID-19 situation and consistent with the relevant literature working on MSCs (e.g., Shen et al. 2021a, Shen et al. 2021b). As a remark, here, the infection probabilities refer to the ones perceived by the consumers, which are different from the chance of infection transmission. The former one mainly depends on the quality of masks, while the latter is related to the number of consumers who use masks, which will be further discussed in Chapter 4.3.3.

Consumers are heterogeneous in their valuation *v* toward masks, which is an unpredictable force for the manufacturer and the government.. Following the standard OM literature, for tractability and simplicity purposes, we use model *v* as a uniformly distributed random variable with a range of [0,1]. Consumers make purchasing decisions on the basis of their utilities, which are related to the price, subsidies (if any), and infection probability: $U_b = v - p + xs - \delta_b(q)$ and $U_{nb} = -\delta_{nb}$, where *p* is the unit retail price, and infection probabilities $\delta_b(q)$ and δ_{nb} are presented as the disutility for consumers. In Model C, we consider *x = 1* and in Model M, we consider *x = 0*, where *x is* a binary variable denoting the subsidy scheme imposed by the government. Only consumers who gain a higher utility for buying masks than not buying, that is, $U_b > U_{nb}$, will purchase. Each consumer purchases one unit in a limited selling period. This setting is consistent with real-world observations that the government restricts consumers' mask consumption for social fairness during the pandemic. The market population is normalized to 1; hence, the actual market demand is given by $d_0 = \int_{p-xs-\tau q}^{1} f(v)dv = 1 - p + xs + \tau q$. Due to the uncontrollable and un-anticipatable supply disruption under COVID-19, only partial demand can in general be satisfied[10]. The expected realized demand is

$$D = E(\tilde{D}) = \theta d_0 = \theta(1 - p + xs + \tau q), \tag{4.1}$$

and (expected) consumer surplus CS can be derived as follows

$$CS = \theta \int_{p-xs-\tau q}^{1} [v - p + xs + \tau q)] f(v)dv = \theta[1 - p + xs + \tau q]^2 / 2, \tag{4.2}$$

where θ represents the supply disruption level (this will be discussed in detail in Chapter 4.3.2).

4.3.2 Production Problem

We consider that the manufacturer's production yield (of good products that pass the production standard) is ε, which represents the percentage of qualified output of masks (Tang and Kouvelis 2011). Unqualified masks $(1-\varepsilon)$ cannot be sold and are valued 0 (e.g., see clarifications in Chapter 4.1.1), which are not subsidized by the government. As a remark, following the literature of quality control, noting that the manufacturer's production yield is the inherent attribute of the production process (Juran and Gryna 2001), we consider the case in which the manufacturer's production yield is exogenously given, irrespective to the product type. Owing to lockdowns of cities and many unexpected labor and resource shortage problems during the COVID-19 outbreak, the manufacturer may suffer losses from supply disruptions. The chance and magnitude of this supply disruption are totally uncontrollable and un-anticipatable by any agent in the MSC. In the presence of this supply disruption, we assume that the manufacturer can only fulfill the order scaled by a random variable $\tilde{\theta}$, where $\tilde{\theta}$ follows a probability density function $g(\tilde{\theta})$ with mean $\theta \in [0,1]$. A smaller θ implies that supply disruption is more severe, and $\theta = 1$ means that no supply disruption occurs (and hence, all the demand can be satisfied). Following observed real practices under the COVID-19 outbreak, $\tilde{\theta}$ is a random variable which means nobody in the MSC would know its value in advance. Facing an actual market demand of d_0, only $\tilde{D} = \tilde{\theta} d_0$ can be satisfied. Taking expectation, we have $D = E(\tilde{D}) = \theta d_0$.

[10] As a remark, our study does not cover the period of the very beginning of COVID-19 when the market environment is out of control. Thus, we argue that it is reasonable to follow the standard literature and consider a linear demand function.

Considering the production yield issue, the expected real production output of masks is $Q = E(\tilde{Q}) = \theta d_0 / \varepsilon$. Following Lee et al. (2019), we consider two kinds of costs afforded by the manufacturer: (i) the unit production cost, which is composed of the fixed cost *k* and the variable cost related to product quality ξq, where ξ is the coefficient of quality on unit production cost, and (ii) the quality improvement cost, which follows an increasing convex function $C(q)$, where $C'(q) > 0$ and $C''(q) > 0$. This setting is also in line with our interview result that the quality of masks depends on both materials (i.e., unit production cost) and equipment (i.e., quality improvement cost) used in production. The directly proportional variable cost (i.e., ξq) indicates a direct cost (such as materials) associated with quality level. The increasing convex improvement cost reflects that the "marginal reduction of cost" increases when quality is improved. For tractability, we assume $C(q) = \lambda q^2 / 2$ in the following analysis (Ma et al. 2018, Katewa and Jain 2022)[11]. The manufacturer decides its selling price *p* and quality level of mask *q* by maximizing its profit listed as follows:

$$\Pi(p,q) = [p + (1-x)s]D - (k + \xi q)Q - \lambda q^2 / 2 . \tag{4.3}$$

Recall that $x = 1$ for Model C and $x = 0$ for Model M.

4.3.3 Government's Problem

Social health risk *R* is reflected by the chance of infection transmission in the whole society. Recall that $\delta_b(q)$ and δ_{nb} denote the infection probabilities for individuals who buy and do not buy masks, respectively. Following Kaplan (2020), we have {The chance of infection transmission} $= 1 - [1 - \delta_j(q)]^n \approx 1 - [1 - n\delta_j(q)] = n\delta_j(q)$, where $n = D$ or $1 - D$ and $j = b$ or nb. It means that if more consumers purchase the mask, the chance of infection transmission will be lower. We derive the social health risk as follows:

$$R = (1-D)\delta_{nb} + D\delta_b(q) . \tag{4.4}$$

Note that (4.4) is consistent with the settings in the literature (e.g., Arifoğlu and Tang, 2022). (i) The infection probability of the individuals who do not buy masks is larger than that of individuals

[11] The main conclusions still hold if the quality improvement cost follows a more general form. Please refer to Xu et al. (2022a) for the details.

who buy masks, i.e., $\delta_{nb}(q) \geq \delta_b(q)$. (ii) The gap between "the health risk across the population" (i.e., $(1-D)\delta_{nb} + D\delta_b(q)$) and "the risk of an individual who uses a mask" (i.e., $\delta_b(q)$) decreases as more people purchase masks. In other words, we have $(1-D)[\delta_{nb}(q) - \delta_b(q)]$ decreases in D. (iii) Each additional use of the mask yields a smaller marginal decrease in the health risk that the use of mask brings relative to the average, i.e., $D[(1-D)\delta_{nb}(q) + D\delta_b(q) - \delta_b(q)]$ is concave in D.

The government makes a subsidizing decision by maximizing the total social welfare, which includes four parts: manufacturer's profit Π, consumer surplus *CS*, social health risk *R*, and government's expenditure. The expenditure of the government consists of the subsidizing cost and implementation cost, i.e., $sd + F_i$. Note that considering the government's cost in operations is rather common in OM (e.g., Caldentey and Mondschein 2003). However, the government's focus or attitude toward these four parts of social welfare may vary depending on the COVID-19 situation as well as its priority. For example, governments with sufficient financial reserve focuses more on the welfare of citizens, whereas those with financial difficulties put more emphasis on the expenditure. To capture this feature, we propose that in general, the weights of these four parts on social welfare, that is,

$$SW(s) = \alpha\Pi + \beta CS - \gamma R - \eta(sD + F_i), \tag{4.5}$$

where $\alpha + \beta + \gamma + \eta = 1$.

To show the validity of our proposed model, Table 4-2 summarizes the important settings that reflect the features of an MSC during the COVID-19 outbreak (P.S.: Detailed descriptions of the features can be checked in Chapter 4.2.2). Notation list of this chapter is shown in Table A4-2 in Appendix A.

Table 4-2. Important features of MSC operations during the COVID-19 outbreak.

Features of MSCs	Corresponding model settings
Supply disruption	Supply disruption (e.g., of materials) exists, that is, only partial demand can be satisfied.
Timely risk prevention	Infection probability and social health risk can be partially reduced by the use of masks.
Varying quality performance in terms of different types of masks	The quality level can be decided by the manufacturer.
Control on production standard	Only qualified products can be sold.

4.3.4 Equilibrium Solutions

In this subchapter, we examine the three possible cases, namely, (i) Model O (benchmark case), in which the government does not provide any subsidy for the MSC (i.e., $s = 0$), (ii) Model C, in which the government subsidizes s_C to the consumers who purchase the mask, and (iii) Model M, in which the government subsidizes the manufacturer's production with an amount of s_M for each qualified mask. Note that, in the basic models, we assume that the manufacturer claims the government subsidy honestly, without announcing the amount of unqualified products. However, the temptation to cut corners, or even to be dishonest, is high (Anjoran 2020). We extend the model by considering manufacturer's dishonest behavior in Chapter 4.5.1. We use subscripts "O", "C", and "M" to denote these three cases, respectively.

According to Equation (4.1), we have the market demand in three cases as follows: $D_i = \begin{cases} \theta(1-p+\tau q), & when\ i = O\ or\ M \\ \theta(1-p+s_C+\tau q), & when\ i = C \end{cases}$. The government decides the optimal subsidy amount in Models C and M by maximizing the total social welfare $SW_i = \alpha\Pi_i + \beta CS_i - \gamma R_i - \eta(s_i D_i + F_i)$, where $i = C\ or\ M$. Afterwards, the manufacturer determines the optimal price and quality by maximizing its profit $\Pi_i = \begin{cases} \max\limits_{(p,q)} pD_i - (k+\xi q)Q_i - \frac{\lambda q^2}{2}, & when\ i = O\ or\ C \\ \max\limits_{(p,q)} (p+s_M)D_i - (k+\xi q)Q_i - \frac{\lambda q^2}{2}, & when\ i = M \end{cases}$. By using backward induction, we yield the equilibrium solutions for each case as shown in Table 4-3. Note that, to ensure the concavity of the objective functions, the condition $\lambda > \theta(\tau\varepsilon - \xi)^2 / 2\varepsilon^2$ should be satisfied for Model O, and conditions $\alpha < \bar{\alpha}$ and $\lambda > \underline{\lambda}$ should be satisfied for Models C and M, where $\bar{\alpha} = (4\eta - \beta)/2$ and $\underline{\lambda} = \frac{\theta(\tau\varepsilon - \xi)[(\alpha - 2\eta)(\tau\varepsilon - \xi) - 2\tau\gamma\varepsilon]}{(2\alpha + \beta - 4\eta)\varepsilon^2}$. These conditions are well-satisfied in the real-world situation: (i) First, the cost of quality improvement for masks should be sufficiently high (i.e., $\lambda > \theta(\tau\varepsilon - \xi)^2 / 2\varepsilon^2$ and $\lambda > \underline{\lambda}$), which means that increasing quality to be infinite is infeasible. (ii) Second, the emphasis on profit in the social welfare function should not too high (i.e., $\alpha < \bar{\alpha}$). This is also in line with the case under the COVID-19 pandemic as the government focuses on consumer welfare and health risk more, rather than profit in MSCs.

Table 4-3. Equilibrium solutions for different Models.

Cases	Equilibrium solutions	Conditions
Model O	$q_O^* = \frac{\theta(\tau\varepsilon-\xi)(\varepsilon-k)}{2\varepsilon^2\lambda-\theta(\tau\varepsilon-\xi)^2}$, $p_O^* = \frac{\varepsilon+k}{2\varepsilon}+\frac{\theta(\tau\varepsilon-\xi)(\tau\varepsilon+\xi)(\varepsilon-k)}{2\varepsilon[2\varepsilon^2\lambda-\theta(\tau\varepsilon-\xi)^2]}$, and $\prod_O^* = \frac{\theta\lambda(\varepsilon-k)^2}{2[2\varepsilon^2\lambda-\theta(\tau\varepsilon-\xi)^2]}$.	$\lambda > \frac{\theta(\tau\varepsilon-\xi)^2}{2\varepsilon^2}$
Model C	$q_C^* \mid s_C = \frac{\theta(\tau\varepsilon-\xi)(\varepsilon-k+\varepsilon s_C)}{2\varepsilon^2\lambda-\theta(\tau\varepsilon-\xi)^2}$, $p_C^* \mid s_C = \frac{\varepsilon+k+\varepsilon s_C}{2\varepsilon}+\frac{\theta(\tau\varepsilon-\xi)(\tau\varepsilon+\xi)(\varepsilon-k+\varepsilon s_C)}{2\varepsilon[2\varepsilon^2\lambda-\theta(\tau\varepsilon-\xi)^2]}$, $s_C^* = \frac{k}{\varepsilon}-1-\frac{\eta(k-\varepsilon)[2\lambda\varepsilon^2-\theta(\tau\varepsilon-\xi)^2]}{\varepsilon\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}}$, $\prod_C^* = \frac{\theta\lambda\eta^2(k-\varepsilon)^2[2\lambda\varepsilon^2-\theta(\tau\varepsilon-\xi)^2]}{2\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}^2}$, and $SW_C^* = \frac{\theta\lambda\eta^2(k-\varepsilon)^2}{2\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}}-\gamma r-\eta F_C$.	$\lambda > \underline{\lambda}$ and $\alpha < \bar{\alpha}$
Model M	$q_M^* \mid s_M = \frac{\theta(\tau\varepsilon-\xi)(\varepsilon-k+\varepsilon s_M)}{2\varepsilon^2\lambda-\theta(\tau\varepsilon-\xi)^2}$, $p_M^* \mid s_M = \frac{\varepsilon+k-\varepsilon s_M}{2\varepsilon}+\frac{\theta(\tau\varepsilon-\xi)(\tau\varepsilon+\xi)(\varepsilon-k+\varepsilon s_M)}{2\varepsilon[2\varepsilon^2\lambda-\theta(\tau\varepsilon-\xi)^2]}$, $s_M^* = \frac{k}{\varepsilon}-1-\frac{\eta(k-\varepsilon)[2\lambda\varepsilon^2-\theta(\tau\varepsilon-\xi)^2]}{\varepsilon\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}}$, $\prod_M^* = \frac{\theta\lambda\eta^2(k-\varepsilon)^2[2\lambda\varepsilon^2-\theta(\tau\varepsilon-\xi)^2]}{2\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}^2}$, and $SW_M^* = \frac{\theta\lambda\eta^2(k-\varepsilon)^2}{2\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}}-\gamma r-\eta F_M$.	

4.4 Analysis: Subsidizing Consumers or Manufacturers

Now, we address an important issue on whether subsidizing consumers or manufacturers is better than the other. To do so, we first compare the results between the cases with and without subsidy (i.e., Model O vs. Model C/M).

Proposition 4.1. *(i)* $q_i^* > q_O^*$ *; (ii)* $p_C^* > p_O^*$ *; whereas* $p_M^* < p_O^*$ *if and only if* $\lambda > \hat{\lambda}$ *, where* $\hat{\lambda} = \frac{\theta\tau(\tau\varepsilon-\xi)}{\varepsilon}$ *and* $\hat{\lambda}$ *is increasing in* τ *; (iii)* $D_i^* > D_O^*$, $CS_i^* > CS_O^*$, $R_i^* < R_O^*$ *and* $\prod_i^* > \prod_O^*$*, where*

i = C or M.

Propositions 4.1(i) and (iii) indicate that providing subsidies not only results in quality improvement but also reduces social health risk as well as benefits the manufacturer and consumers by increasing the market demand, regardless of the type of subsidy. The results clearly imply that consumer and manufacturer subsidy programs are valuable and advisable for the MSC during the COVID-19 outbreak. The subsidies not only help prevent the spread of virus efficiently by improving mask quality but also increase each supply chain member's benefit. This finding is consistent with the interview results, which implies that the government subsidy can increase the production to match the increased demand during the pandemic (see Table 4-1). Nonetheless, the pricing strategy differs under the two subsidy programs. The manufacturer tends to raise the price if the government subsidizes consumers directly (i.e., Model C). This result is intuitive as consumer subsidy can enhance consumers' willingness to buy. When the government subsidizes the manufacturer directly (i.e., Model M), the manufacturer will lower the price if the coefficient of quality improvement cost is sufficiently large. The potential reason is that the quality improvement cost discourages quality improvement (i.e., $\frac{d(q_M^*|s_M)}{d\lambda} = -\frac{2\varepsilon^2\theta(\tau\varepsilon-\xi)(\varepsilon-k+\varepsilon s_M)}{[2\varepsilon^2\lambda-\theta(\tau\varepsilon-\xi)^2]^2} < 0$), as a result, demand increase from quality improvement is limited. Therefore, the manufacturer will set a lower price to increase the demand when the quality improvement cost is too high. Besides, price reduction is likely to happen in Model M when the original infection rate is low. As the original infection rate increases, high-quality masks with a high price are produced to prevent the spread of the highly infectious disease.

Proposition 4.2. *(i)* $s_C^* = s_M^* = s^*$, $q_C^* = q_M^*$, *and* $p_C^* - p_M^* = s^*$. *(ii)* $\prod_C^* = \prod_M^*$, $CS_C = CS_M$, $R_C = R_M$ *and* $SW_C - SW_M = \eta(F_M - F_C)$.

From Proposition 4.2, we can see that implementing the subsidy scheme in Models C and M has the same impact on masks quality, the manufacturer's profit, consumer surplus, and social health risk. This is because the reduction of prices is equal to the government's unit subsidy, which leads to the same market demands as well as the profits under two subsidy programs. This result is consistent with findings reported in the prior literature (e.g., Berenguer et al. 2017 and Yu et al. 2020). Note that our study characterizes subsidy implementation cost and evaluates the impacts of subsidy programs on social welfare. In common practices, implementing the subsidy program incurs a non-trivial cost. Besides, we interestingly find that our results provide new insights compared with Taylor and Xiao

(2014), which would predict that Model C is superior to Model M when the market demand is uncertain. In our study, we also consider the existence of uncertainty, i.e., random consumer valuation.

In terms of social welfare, Proposition 4.2(ii) shows that a low subsidy implementation cost can lead to high social welfare, and the amount of social welfare improvement is directly proportional to the difference between the fixed costs of implementing the subsidy programs. Our findings indicate that the government should use the subsidy scheme with a lower implementation cost.

Proposition 4.3. $\prod_i^*, CS_i^*$*, and* SW_i^* *increase in* θ*, whereas* R_i^* *decreases in* θ*, where i=C or M.*

Disruption risks arise in MSCs during the COVID-19 pandemic due to the unexpected labor and resource shortage problems. Recall that a higher θ means a lower disruption risk. Proposition 3 shows that supply disruption harms the supply chain profit, consumer surplus, social health risk, and social welfare. Hence, the government must take measures to prevent supply disruption. This result is consistent with the real practice during the COVID-19 outbreak. For example, the Chinese government recognized the importance of controlling raw materials of masks. They launched the information sharing platform for raw materials of masks at the early stage of COVID-19 outbreak, under which the demand can be better matched with the supply. This result also explains why the interviewee's firm, i.e., *Foshan Nanhai Beautiful Nonwoven Co., Ltd*, has its own raw material production line since it can prevent the MSC from facing a serious supply disruption.

We intend to further explore the value of subsidy programs on the MSC. We define $\Delta\prod=\prod_i^*-\prod_O^*$, $\Delta CS=CS_i^*-CS_O^*$, $\Delta R=R_i^*-R_O^*$, and $\Delta SW=SW_i^*-SW_O^*$, where i = C or M, as the values of subsidy program. We conduct numerical studies to evaluate the joint impact of supply disruption and original infection rate. All the data in the numerical studies satisfy the respective physical meanings and follow the model assumptions. We summarize the results in Table 4-4, and all details can be found in Table A4-3 in Appendix A.

Table 4-4 reveals that the adoption of subsidy program can increase benefits to the manufacturer and consumers as well as decrease social health risk when the original infection rate increases, regardless of the intensity of supply disruption. Moreover, supply disruption affects the subsidy program's value on social welfare. Specifically, when the disruption is weak, the subsidy program is less valuable to combat the high original infection rate. The potential reason is that under weak disruption and high infection rate, most consumers can purchase masks successfully, which results in relatively high social welfare. Consequently, minimal improvements can be made in the supply chain through the subsidy program. As the intensity of disruption increases, the subsidy program becomes more valuable. As we can see, when the disruption level is moderate, social welfare first increases and then decreases with the infection rate; when the disruption level is high, a higher infection rate always increases social welfare under the subsidy program. The potential reason behind is that the subsidy program can improve mask production, which relieves unavailability of masks caused by the strong disruption when the original infection rate is high. However, the subsidy program is less effective when the disruption risk is weak, because the government has to pay a large amount of money to satisfy the huge production quantity. Therefore, we can infer that the subsidy program can be helpful and effective when facing highly infectious diseases like COVID-19, especially when inevitable supply disruption is strong. Note that, in practice, the disruption degree could be dynamic. When facing the situation where the disruption degree suddenly changes from strong to weak, it is government's responsibility to control the infection rate at a low level to avoid the deterioration of social welfare. Whereas when the disruption degree suddenly changes from weak to strong, surprisingly, it is unnecessary to control the infection rate as the social welfare will not be hurt. Besides, the results indicate that in the post-pandemic stage, in which both original infection rate and supply disruption are relatively low, the subsidy program is no longer effective for social welfare. That is the reason why in real world cases (see interview results in Table 4-1), Chinese government cancelled the subsidy program in August 2020 when the pandemic is basically in control.

Table 4-4. Impacts of original infection rate τ on MSC performance with supply disruption.

Performance	Weak disruption	Moderate disruption	Strong disruption
$\Delta\Pi$		↑	
ΔCS		↑	
ΔR		↓	
ΔSW	↓	↑↓	↑

Remark: "↑" means "increase" in τ, "↓" means "decrease" in τ, and "↑↓" means "first increase and then decrease" in τ

We summarize our findings in the basic model and generate Managerial Insight 1.

Managerial Insight 4.1 (To subsidize consumers or manufacturer). *(i) Models C and M are equivalent in terms of consumers' and manufacturer's benefits. (ii) A low subsidy implementation cost* *can lead to high social welfare. (iii) The subsidy program is efficient in increasing consumer surplus as well as reducing harm on social health risk and the whole supply chain brought by highly infectious diseases like COVID-19.*

Managerial Insight 4.1 provides several important implications and shows the efficiency of government subsidies for the MSC under the COVID-19 outbreak: (i) Consumer and manufacturer subsidies can improve the MSC performance equally. Thus, the government should subsidize the scheme that is easier and cheaper to implement in practice. (ii) The subsidy program is efficient in reducing the negative effects caused by COVID-19. Under the COVID-19 pandemic, the inevitable supply disruption and high production cost (owing to labor and resource shortage problems) are critical issues for the MSC. Supply disruption under pandemic can harm supply chain performance. The government's subsidy program can make up for the loss of supply chain members and consumers. Thus, the government should manage the raw materials of masks in the early stage of pandemic to avoid supply disruption. If disruption is happening, then the subsidy program with a lower implementation cost is recommended.

4.5 Extended Analyses: Control More or Less?

4.5.1 Dishonesty Prevention Policy

In this subchapter, focusing on the manufacturers, the dishonesty prevention policy is proposed to address the key issue of dishonest behavior under the subsidy scheme. The dishonesty prevention policy is actually rather common. For instance, in a city like Hong Kong, the government requires the manufacturers applying for subsidies for producing masks under COVID-19 to submit evidence of their production capacity and conducts on-site monitoring for those approved production lines (Hong Kong Productivity Council 2020).

Note that in the basic model, we assume that the manufacturer honestly announces the output and claims subsidy in Model M. However, under the manufacturer subsidy scheme, a manufacturer may over-claim its output to enjoy "free lunch" on the increased subsidies and makes up for its loss brought by the yield problem. Thus, for real-world implementation, the manufacturer's dishonest behavior is worthy of attention. If the government (e.g., like the Hong Kong government) wants to avoid dishonesty, proper monitoring should be imposed to prevent dishonesty in Model M. In this subchapter, in the context of a dishonest manufacturer, three possibilities are proposed: (i) the government fully anticipates manufacturer's dishonest behavior, (ii) the government "does not attempt to anticipate" manufacturers' dishonest behavior, and (iii) blockchain is used to fully avoid manufacturer's dishonest behavior. Blockchain is an emerging, innovative, and disruptive technology that can lessen the risk of dishonesty by providing transparent and permanent records that can be verified (Babich and Hilary 2020). With the implementation of blockchain, the manufacturer is deterred from dishonesty since it will need to bear a serious consequence if the dishonest behavior is found upon inspection with respect to the permanent record in the blockchain.

(A) Dishonesty Anticipated: Case A

We first explore the case where the government fully anticipates the manufacturer's dishonest behavior. This setting is essentially consistent with "rational expectation theory," which indicates that in a market, rational individuals possess an expectation that is equivalent to the reality provided by the market. This theory has been widely adopted in OM domain (e.g., Tereyağoğlu and Veeraraghavan 2012, Ahn et al. 2016). Under this scenario, the manufacturer over-claims its output to receive additional subsidies for those unqualified masks. The profit function is $\hat{\Pi}_M^A = p^A D_M + s_M^A Q_M - (k + \xi q^A) Q_M - \frac{\lambda (q^A)^2}{2}$. Recall that Q_M refers to the expected real production output of masks (including those unqualified ones), which should be larger than the real qualified output (which is equivalent to the realized demand in our deterministic model setting) D_M, and it can be expressed as $Q_M = D_M / \varepsilon = \theta d_0 / \varepsilon$. The government expects this scenario and grants subsidies to maximize social welfare $\hat{S}W_M^A = \alpha \hat{\Pi}_M^A + \beta CS_M^A - \gamma R_M^A - \eta (s_M^A Q_M + F_M)$. We use superscript "A" to represent this case and derive Proposition 4. All the equilibrium solutions are given in Table A4-4 in Appendix B.

Proposition 4.4. *(i)* $\hat{q}_M^{A*} = q_M^*$, $\hat{p}_M^{A*} = p_M^*$, *and* $\hat{s}_M^{A*} < s_M^*$. *(ii)* $\hat{C}S_M^{A*} = CS_M^*$, $\hat{\Pi}_M^{A*} = \Pi_M^*$, $\hat{R}_M^{A*} = R_M^*$ *and* $\hat{S}W_M^A = SW_M$.

We surprisingly find that when the manufacturer's dishonest behavior can be fully anticipated by the government, the dishonest behavior interestingly does not harm social health and reduce the profit of supply chain members because the government can achieve the optimal social welfare by reducing the subsidy amounts. As a result, even if a manufacturer over-claims its output, it cannot earn more from such a dishonest behavior.

(B) Dishonesty Not Anticipated: Case NA

Suppose that under this case, the government does not attempt to anticipate the manufacturer's dishonest behavior (use superscript "NA" to represent). It means that the government assumes the manufacturer to be honest and does not change its subsidy amount, i.e., $s_M^{NA*} = s_M^*$. Meanwhile, the manufacturer also does not change any decisions based on the previous results in the basic model, i.e., $q_M^{NA*} = q_M^*$ and $p_M^{NA*} = p_M^*$, as any modifications on decisions will expose its dishonest behavior. However, since the manufacturer will over-claim its output to include those unqualified masks, the manufacturer's profit function is expressed as $\hat{\Pi}_M^{NA} = p^{NA} D_M + s_M^{NA} Q_M - (k + \xi q^{NA}) Q_M - \frac{\lambda (q^{NA})^2}{2}$, and the corresponding social welfare becomes $\hat{S}W_M^{NA} = \alpha \hat{\Pi}_M^{NA} + \beta CS_M^{NA} - \gamma R_M^{NA} - \eta (s_M^{NA} Q_M + F_M)$.

Proposition 4.5. $\hat{C}S_M^{NA*} = CS_M^*$ *;* $\hat{R}_M^{NA*} = R_M^*$ *;* $\hat{\Pi}_M^{NA*} > \Pi_M^*$ *;* $\hat{S}W_M^{NA} < SW_M$ *if and only if* $\eta > \alpha$ *; otherwise,* $\hat{S}W_M^{NA} \geq SW_M$.

Proposition 4.5 reveals that if the government cannot exactly foresee the manufacturer's dishonest behavior, then it is intuitive that the manufacturer can benefit from over-claiming the amount of output as it can enjoy "free lunch" on the increased subsidies. However, it makes no difference for consumer surplus and social health risk because the price and mask quality remain unchanged. Moreover, dishonest behavior may harm social welfare if the government pays more attention to financial expenditure rather than manufacturer's profit. This is because the government offers additional subsidies to the manufacturer who is dishonest. If the government is indifferent to expenditure, a win–win situation can be realized despite the dishonest behavior. This may explain why some governments, such as those with sufficient resources, vote for subsidizing manufacturers even though dishonest behaviors may occur.

(C) Using Blockchain: Case BNA

The government may take effective measures to prevent dishonesty. However, the traditional way of monitoring (e.g., on-site monitoring) is costly, and may not be effective to address data fraud. At present, blockchain technology has been proved to be an efficient tool to eliminate dishonesty by providing traceable and transparent information (Chang et al. 2018, Hastig and Sodhi 2020). It also reduces the infection risk of people who visit factories during the pandemic. Thus, in this subchapter, we propose to use blockchain as a tool for the government to prevent dishonest behavior from happening. One argument is that, if "dishonesty prevention" can help improve social welfare, then manufacturers should be encouraged to implement blockchain based production systems, i.e., subsidies will not be provided for manufacturers who do not adopt blockchain. Using blockchain includes a unit implementation cost c_{BNA} and a fixed operations cost F_{BNA}, which are paid by the manufacturer[12]. The manufacturer's profit is $\hat{\Pi}_M^{BNA} = (p^{BNA} + s_M^{BNA} - c_{BNA})D_M - \frac{\lambda(q^{BNA})^2}{2} - (k + \xi q^{BNA})Q_M - F_{BNA}$, and social welfare is $\hat{S}W_M^{BNA} = \alpha\hat{\Pi}_M^{BNA} + \beta CS_M^{BNA} - \gamma R_M^{BNA} - \eta(s_M^{BNA}D_M + F_M)$. We use superscript "BNA" to represent this scenario and show the equilibrium results in Table A4-4 (Appendix B).

Recall that under the case of anticipation (i.e., Case A), the manufacturer's dishonest behavior does not harm the MSC (refer to Proposition 4.4). As a result, the government has no incentive to require blockchain implementation. Only when dishonest behavior is unpredictable for the budget-limited government (i.e., Case NA and $\eta > \alpha$) should it be wise to implement a dishonesty prevention scheme (i.e., request blockchain implementation). We hence only explore this case when analyzing the value of using blockchain; for other cases, there is no incentive for the government to implement blockchain for preventing dishonesty.

Proposition 4.6. $\hat{C}S_M^{BNA*} < \hat{C}S_M^{NA*}$; $\hat{R}_M^{BNA*} > \hat{R}_M^{NA*}$; $\hat{\Pi}_M^{BNA*} < \hat{\Pi}_M^{NA*}$; $\hat{S}W_M^{BNA*} > \hat{S}W_M^{NA*}$ *if and only if* $F_{BNA} < F'_{BNA}$.

From Proposition 4.6, we see that using blockchain can improve social welfare for the government who pays more attention to financial expenditure (i.e., $\eta > \alpha$) if the blockchain implementation cost is not too high (i.e., $F_{BNA} < F'_{BNA}$). However, using blockchain hurts consumers' and manufacturer's benefits as well as increases social health risk. The reason is that the manufacturer cannot over-claim the output to gain "free lunch" and hence they would reduce mask quality correspondingly. In short, using blockchain can eliminate the negative effect on social welfare brought by the manufacturer's dishonest behavior, while sacrificing consumers' and manufacturer's benefits.

To summarize, we illustrate the impact of the dishonest manufacturer under three cases in Table 4-5, which highlights the value of dishonesty prevention (Case BNA). Our analytical results imply that the government should consider the financial situation and blockchain implementation cost when choosing the subsidy plan to help consumers or manufacturer.

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[12] Note that, the fixed operations cost F_{BNA} can be also paid by the government in practices. However, it is straightforward that the optimal solutions are remain unchanged as they are independent on F_{BNA}. Besides, we notice that the efficiency of using blockchain is also not affected as well, we hence do not include this case here to avoid repetition.

Table 4-5. Impacts of dishonest manufacturer under Cases A, NA, and BNA.

Case	Manufacturer's profit	Consumer surplus	Social health risk	Government welfare
Case A	No change	No change	No change	No change
Case NA	Always benefit	No change	No change	Benefit if $\eta \le \alpha$ but hurt if $\eta > \alpha$
Case BNA	Always hurt	Always hurt	Always hurt	Benefit if $F_{BNA} < F'_{BNA}$ and $\eta > \alpha$

To provide supply chain members with useful insights when using blockchain, we explore the influences of production cost on the use of blockchain in Proposition 4.7. We define $\Delta\hat{CS}_M = \hat{CS}_M^{BNA*} - \hat{CS}_M^{NA*}$, $\Delta\hat{R}_M = \hat{R}_M^{BNA*} - \hat{R}_M^{NA*}$, $\Delta\hat{\prod}_M = \hat{\prod}_M^{BNA*} - \hat{\prod}_M^{NA*}$, and $\Delta\hat{SW}_M = \hat{SW}_M^{BNA*} - \hat{SW}_M^{NA*}$ as the values of using blockchain for consumers, the manufacturer, and the government, respectively.

Proposition 4.7. $\Delta\hat{CS}_M$ *increases in k,* $\Delta\hat{R}_M$ *decreases in k,* $\Delta\hat{\prod}_M$ *is concave in k, and* $\Delta\hat{SW}_M$ *is convex in k.*

Proposition 4.7 reveals the impacts of the fixed production cost on the value of blockchain. First, recall that Proposition 4.6 shows that the use of blockchain always harms consumer surplus and increases social health risk, whereas Proposition 4.7 uncovers that the negative impacts of blockchain implementation on these two aspects can be reduced if the fixed production cost increases. From the manufacturers' side, as the value of blockchain is concave in *k*, using blockchain brings the highest value if the production cost is neither sufficiently high nor small. Moreover, the value brought by blockchain is convex in terms of social welfare. This result implies that the best social welfare appears on the boundaries in which the fixed production cost is either very high or low. Nevertheless, blockchain technology can be more valuable for the MSC with a higher fixed production cost than that with a lower cost since the use of blockchain improves social welfare more, which can compensate the reduction of consumer surplus and social health risk.

Managerial Insight 4.2 (To prevent dishonesty or not). *(i) If the government can accurately anticipate dishonest behaviors of manufacturers when it makes a decision on the type of subsidy, then the government does not have an incentive to prevent dishonesty by implementing blockchain technology. By contrast, if the government cannot accurately anticipate dishonest behaviors, then the decision to prevent dishonesty or not depends on the relative emphasis that the government places on financial expenditure versus manufacturer's profit. (ii) Using blockchain can prevent dishonesty and* *eliminate the negative effect on social welfare (brought by the manufacturer's dishonest behavior). Adopting blockchain technology is more valuable for the MSCs to sell high-cost masks.*

4.5.2 Price Control Policy

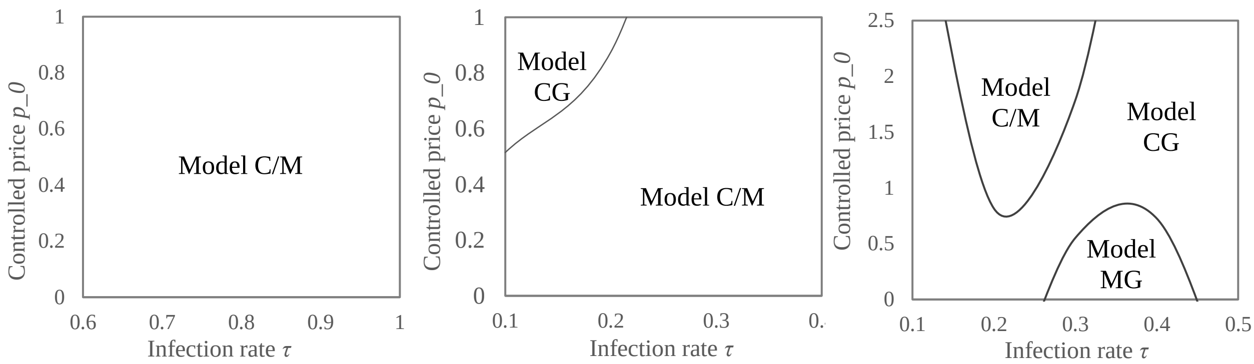
In this subchapter, we extend the model to explore the case under which the price of masks is controlled by the government at a certain level, instead of being freely set by the manufacturer. The price control policy is commonly regarded as a policy for the benefit of consumers (i.e., focusing on consumers). The standard argument is that imposing the price control policy avoids "crazily" inflated pricing which affects consumer welfare. However, is it really true? We address this issue in the following.

During the COVID-19 outbreak, supply disruption is significant and demand for masks is high. Thus, the supply is difficult to match with demand. This challenge leads to price speculation and hoarding in the mask market. To avoid such an unhealthy market environment, a price control policy has been implemented in a number of countries during the COVID-19 outbreak (e.g., Italy, Mainland China, and Thailand). This is also verified by our interview results (see Table 4-1). To analytically examine the impact of controlled price, we consider the case in which the price of masks is exogenously set at p_0. This price can be the selling price of mask before COVID-19 happened or a price advised by the government. On the basis of this given price, the government first grants subsidies to the manufacturer or consumers. Then, the manufacturer follows and decides the quality level. Similar to the basic model, three extended models are considered: (i) Model OG: without government subsidies under the controlled price, (ii) Model CG: government subsidizes consumers under controlled price, and (iii) Model MG: government subsidizes the manufacturer under the controlled price. Table A4-5 in Appendix B provides all the equilibrium solutions.

Proposition 4.8. *(i)* $q_{CG}^* < q_{OG}^*$ *and* $q_{MG}^* > q_{OG}^*$. *(ii)* $CS_i^* > CS_{OG}^*$ *and* $R_i^* < R_{OG}^*$, *where i = CG or MG. (iii)* $\prod_{MG}^* > \prod_{OG}^*$, *whereas* $\prod_{CG}^* > \prod_{OG}^*$ *if and only if* $s_{CG}^* > s'_{CG}$, *where* $s'_{CG} = \frac{[(k-p_0\varepsilon)(\varepsilon\lambda+\theta\xi\tau)-\theta\xi^2(1-p_0)]}{\theta\xi^2}$.

Recall that in the basic model, government subsidies can always improve MSC performance (please revisit Proposition 4.1). However, Proposition 4.8 shows different results under the controlled price case. First, although the government subsidies are efficient to improve consumer surplus and reduce social health risk under the price control policy, Model CG leads to quality reduction because the manufacturer lowers its cost to ensure its benefit. Consequently, subsidizing consumers is no longer preferable for the government as fewer consumers will make purchases because of the reduced quality. Only when the government subsidy is relatively large, the manufacturer would benefit. Otherwise, the manufacturer suffers. In summary, if the price is controlled by the government, then only well-designed subsidies are welcomed by the MSC.

Next, we conduct numerical studies to compare the performance in Models C, M, CG, and MG. We set the same implementation cost in Models C and M because we want to focus on the impact of pricing control and disregard the influence brought by implementation cost.



(a) Optimal strategy for CS (b) Optimal strategy for profit (c) Optimal strategy for SW

Figure 4-1. Optimal subsidy structure for MSC (we set $\alpha = \beta = \gamma = 7/30$, $\eta = 0.3$, $\theta = 0.8$, $\varepsilon = 0.8$, $\xi = 0.1$, $\lambda = 0.3$, $F_{M/C} = 0.1$[13]).

Figure 4-1 provides numerous interesting insights. First, the price control policy is surprisingly not beneficial to consumers under the subsidy program. The reason is that under the price control policy, the manufacturer cannot set a high price for masks, and it is likely to reduce quality to ensure its profit, which eventually harms consumers' benefits. Second, the price control policy is detrimental for the manufacturer when the controlled price is small as the low price harms the manufacturer's profit. When the controlled price is high, Model CG (i.e., Model C with controlled price) is the most profitable strategy for the manufacturer if the original infection rate is sufficiently low. In terms of social welfare, the price control policy is preferable in most cases, except for the case when the original infection rate is low and the controlled price is high. The potential reason is as follows. A low infection rate and a high controlled price reduce market demand significantly, which not only hurts consumers' benefits but also increases the social health risk (because fewer individuals buy and wear masks).

[13] All the data used in the numerical studies (Figures 4-1(a) – 4-1(c)) satisfy the respective physical meanings and follow the model assumptions.

Besides, the controlled price set under the consumer subsidy should be higher than that under the manufacturer subsidy. In summary, we uncover the counter-intuitive result that the price control policy is unwelcomed by consumers under the subsidy program, while it improves social welfare in the case with highly infectious diseases like COVID-19.

We summarize our findings for the price control policy in Managerial Insight 4.3, which provides scientific insights on the pros and cons of imposing price control.

Managerial Insight 4.3 (To control price or not). *(i) The consumer subsidy program is no longer efficient under the price control policy when the subsidy provided by the government is relatively low. (ii) The price control policy can benefit the manufacturer when the original infection rate is not too high; but a bit surprisingly it is always unwelcomed by consumers. (iii) The government is not recommended to impose price control if the original infection rate is relatively low (because social welfare is likely to be hurt); if the original infection rate is sufficiently high, it is wise to impose price control and the controlled price should be higher under the consumer subsidy scheme than that under the manufacturer subsidy counterpart.*

4.6 Summary

4.6.1 Concluding Remarks

Highly infectious diseases like COVID-19 challenge social healthcare. During the outbreak of COVID-19, granting subsidies is an efficient means for the government to intervene the MSC operations and improve social welfare. In this paper, motivated by the industrial news and interview results, we propose a theoretical model to explore how the government should use a subsidy program to enhance the MSC under the COVID-19 outbreak. We establish a three-echelon supply chain wherein the government aims at maximizing social welfare and chooses the subsidy scheme (i.e., either grants subsidies to consumers (Model C) or manufacturers (Model M)). We aim to investigate the joint impact of supply disruption and original infection rate on supply chain performance under both subsidies. Our results verify the performance of different subsidy schemes for MSCs during the COVID-19 outbreak. Moreover, consistent with the real practices during the outbreak of COVID-19 in many places, we extend the model to evaluate the government's different control and intervention policies under a subsidy program from both the manufacturer's and consumer's perspectives, including the dishonesty prevention policy and price control policy. Note that, the current model can be also valuable for dynamic decisions, because it can reflect the MSC performance for a specific moment (e.g., climbing period or peak period); if the decision-makers want to adjust their decisions with time or under specific conditions, they can change a set of data at that specific moment and derive new findings to respond the situation of COVID-19.

4.6.2 Managerial Implications

On the basis of our analytical and numerical results, we provide the following managerial implications for each member of the MSC, namely, consumers, manufacturer(s), and the government, depending on the attainable and measurable data (including the fixed implementation cost of subsidy scheme, the original infection rate of disease, etc.). Note that, these data are the open information or could be measured by the decision-makers, we hence believe that the following proposed managerial implications are valuable and meaningful for the real-world practices. Besides, the current model can be also valuable for dynamic decisions, because it can reflect the MSC performance for a specific moment; if the decision-makers want to adjust their decisions with time or under specific conditions, they can simply change a set of data to derive new findings. We summarize each member's preference for different policies in an evaluation graph in Table 4-6.

For consumers: (i) Consumer and manufacturer subsidies are equally welcomed by consumers. As a result, consumers should not complain (*resp.* feel delighted) if the government decides to subsidize manufacturers (*resp.* the consumers directly). (ii) The deployment of blockchain technology as well as the implementation of price control policy, surprisingly, are unwelcomed by consumers. This counter-intuitive result is mainly due to quality reduction problems. With quality reduction, consumers are hurt because of the higher infection probability under COVID-19. Hence, consumers should not feel happy if these policies are implemented under COVID-19.

For manufacturers: (i) Consumer and manufacturer subsidies are equally welcomed by manufacturers in terms of the increased demand and profit. This finding is basically consistent with our interview results (see Table 4-1) and the managerial insights reported in prior studies (such as Berenguer et al. 2017 and Yu et al. 2020), while gives new insights compared to Taylor and Xiao (2014) for the case with market uncertainty. Besides, unlike the extant literature and specific to the virus outbreak case, we find that the manufacturer will benefit from a higher original infection rate if supply disruption is strong. This interesting result deserves the manufacturers' attention. (ii) Under the case with blockchain deployment, it is understandable that the manufacturer's profit can deteriorate because over-claiming of subsidies for mask output no longer exists. (iii) When the controlled price is high, Model CG (i.e., Model C with the controlled price) is the most profitable strategy for the manufacturer during the COVID-19 outbreak, but the low controlled price can harm the manufacturer's profit under the subsidy program. This result is an important finding because the optimal subsidy scheme should depend on the situation of individual manufacturers and the original infection rate during the COVID-19 outbreak.

***For governments and policy makers*:** (i) A low subsidy implementation cost leads to high social welfare. Hence, the decision rule provided for the government is to conduct the subsidy scheme that is cheaper (in terms of the fixed cost) to implement. This measure is valuable in many places. The government may overlook this important point, which prevents the subsidy program from achieving the optimal level because unnecessary expenses are incurred without bringing any real benefits. Referring to Table A4-1 (Appendix A), both Singapore and Mainland China adopt the consumer subsidy scheme for MSCs under COVID-19. This observation is consistent with our finding, as the acceptance of the mobile payment in these two places is relatively high, which makes it easier and cheaper for the government to track consumers and provide subsidies. For other places, it is more convenient to subsidize manufacturers in the current stage while governments could consider to change their subsidy scheme based on their situations in the future. (ii) The subsidy schemes are no longer effective for social welfare in the post-pandemic stage, when both original infection rate and supply disruption are relatively low. This finding is in line with our interview results that the Chinese government has cancelled the subsidy program in August 2020 when the pandemic is basically in control (see Table 4-1). (iii) Considering the potential existence of dishonest manufacturers under the manufacturer subsidy program, there is no need for the government to prevent dishonesty if the government can well anticipate the dishonest behavior. Even if the government cannot anticipate the manufacturer's dishonest behavior, the government who has adequate financial resources should still "turn a blind eye" on the dishonest behavior; for those governments which have serious concerns regarding the expenditures of subsidies (e.g., countries which face limited budgets or their citizens/officials have lots of concerns on budget fairness, etc.), they are recommended to use blockchain to help eliminate the negative effect on social welfare brought by the dishonest behavior.

Hence, "knowledgeable" governments that can accurately estimate dishonest behaviors do not need to encourage the manufacturer to use blockchain. If governments are less "knowledgeable" and they have concerns on subsidy expenses, then requesting the manufacturer to use blockchain becomes a good solution. (iv) The price control policy is not always the optimal choice for the government when a subsidy program is implemented, as it may hurt the effectiveness of the subsidy program. That may be the reason why most of the governments, e.g., Hong Kong, Japan, Singapore, Germany, etc., do not implement the price control policy under COVID-19 (refer to Table A4-1 in Appendix A). In terms of social welfare, governments are not recommended to impose price control if the original infection rate is low; while in places where the original infection rate of COVID-19 is high, implementing the price control policy is preferable. In addition, the controlled price should be higher under the consumer subsidy program than under the manufacturer subsidy.

In summary, subsidy programs (consumer and manufacturer subsidies) to MSCs are efficient in combating the challenges brought about by the COVID-19. The proper use of blockchain technology and price control policy can improve the overall performance of the MSC but would lead to a sacrifice of consumers' benefit.

Table 4-6. Evaluation graph of different policies for each supply chain member under COVID-19.

<table>
<tr><th>Supply chain members</th><th>Subsidy program</th><th>Dishonesty prevention policy</th><th>Price control policy</th></tr>
<tr><td>Consumers</td><td rowspan="3">🙂</td><td rowspan="2">☹️</td><td>☹️</td></tr>
<tr><td>Manufacturer(s)</td><td rowspan="2">😐</td></tr>
<tr><td>Government</td><td>😐</td></tr>
</table>

Remarks: 🙂 Always preferred 😐 Preferred in some conditions ☹️ Always not preferred

Chapter 5 Ordering COVID-19 Vaccines for Social Welfare with Information Updating[14,15]

5.1 Problem Description

5.1.1 Motivation and Background

December 2019, the COVID-19 pandemic has led to 5.96 million deaths worldwide. In controling the pandemic and restoring normal operations, vaccination is one of the most effective ways (Pauly, 2005; Arifoğlu and Tang, 2022; Duijzer et al., 2018). By June 2021, the World Health Organization (WHO) had cleared eight COVID-19 vaccines developed by Pfizer-BioNTech, AstraZeneca, Moderna, Sinovac, and others for emergency use (WHO Guidance Document, 2021). That means these vaccines can go into people's arms and be sold to other countries. Meanwhile, another eleven vaccine manufacturers are still under processing and could be cleared for use in the future. Note that the efficacy of different vaccines varies. For example, Pfizer-BioNTech's vaccine has a 95% efficacy to protect against confirmed COVID-19; Moderna's vaccine achieves a 94.1% overall efficacy and the efficacy of Johnson & Johnson's vaccine is 72% (Katella, 2021).

Facing pandemics, social welfare should be given the priority when governments make decisions (Ivanov and Dolgui, 2020a). Here, in such a humanitarian problem, social welfare refers to the total surplus of society focusing on people's welfare rather than the enterprise's profit (Deo and Corbett, 2009). A government that aims to improve social welfare should carefully decide on vaccine procurement based on factors such as the infection rate, vaccination demand, and transportation conditions. Moreover, the vaccine demand faces high uncertainty due to the prevalence and severity of unpredictable infectious disease activities (Cho and Tang, 2013; Song et al., 2018; Martin et al., 2020). It is a big challenge for the government when deciding to order vaccines. For instance, in the early stage of a pandemic, only a first vaccine is approved, not a second one. Then the government faces a two-stage ordering problem of deciding the order quantity of the first vaccine at stage one and

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[14] A part of this chapter has been accepted by: "Xu, X., Sethi, S.P., Chung, S.H., Choi, T.M. (2023). Ordering COVID-19 vaccines for social welfare under information updating: Optimal order policy and supplier selection in the digital age. IISE Transactions, forthcoming"

[15] The notations used in this chapter are self-contained and only valid for this chapter.

the order quantities of both vaccines at stage two. It was the typical problem faced by various governments during the initial wave of the COVID-19 pandemic. The Japanese government first noticed the availability of AstraZeneca's vaccine and preordered 120 million doses in August 2020 (first stage). Two months later, in October 2020, when the Moderna's vaccine was rolled out to the market, the government decided to make a supplement order of 50 million doses of the Moderna vaccine (second stage). The US Department of Health and Human Services and the Department of Defense also adopted this two-stage ordering mode. They first ordered 400 million doses of the COVID-19 vaccine from Pfizer in February 2021 (first stage). They then placed an additional order of 100 million from Johnson & Johnson in March 2021 (second stage) (U.S. Department of Health & Human Services, 2021). The European Union (EU) and Taiwan also saw a similar two-stage ordering situation. We summarize the details of governments' vaccine ordering policies in Table 5-1. As we can see, this kind of two-stage vaccine ordering problem is common, especially during the early stage of the pandemic. In addition to the early stage of the pandemic, a similar problem regarding vaccine ordering also appears in the other stages. For example, in February 2022, the Hong Kong government faced the vaccine shortage problem due to the unexpected fifth wave of COVID-19 in Hong Kong. In the early stage, the Hong Kong government had reached agreements with Sinovac and BioNTech to order a total of 7.5 million vaccine doses in December 2020. However, when recently facing a sudden surge in vaccine demand, the supply of vaccines fell well short of demand, causing challenges.

Table 5-1. Real-world governments' vaccine ordering practices.

Regions	Vaccine manufacturers	Efficacy	Ordered doses	Order time	Stage
European Union	Johnson & Johnson	72%	200 million	October 2020	First
	Pfizer-BioNTech	95%	200 million	January 2021	Second
Japan	AstraZeneca	76%	120 million	August 2020	First
	Moderna	94%	50 million	October 2020	Second
Taiwan	AstraZeneca	76%	10 million	November 2020	First
	Moderna	94%	5 million	February 2021	Second
U.S.	Pfizer-BioNTech	95%	200 million	February 2021	First
	Johnson & Johnson	72%	100 million	March 2021	Second

To combat the challenges mentioned above, dynamic ordering policies with demand information updating and a proper use of digital technologies would be helpful (Huang et al., 2005; Erhun et al., 2008). The dynamic ordering policy means that the decision-maker can first make an order by using historical data or expert advice (which usually lacks precision) and then make an additional order decision with an improved vaccine demand forecast (e.g., reordering or changing the vaccine manufacturer). The advantages of this policy have been widely discussed in the prior literature, e.g., it can help better match supply and demand (Choi et al., 2003; Cachon and Swinney, 2011) and increase the government's flexibility (Choi et al., 2018) to ensure that sufficient vaccines are available. Moreover, we notice that the pattern of vaccine selection varies from region to region. Some governments ordered vaccines of lower efficacy in the first stage and then changed to one of a higher efficacy in the second stage (e.g., EU, Japan, and Taiwan). Others followed an opposite pattern, i.e., ordering the higher efficacy vaccines first and then ordering the lower efficacy ones in the second stage (e.g., the U.S.). The reason why they adopted different patterns motivated us to explore the vaccine ordering problem theoretically.

Besides the ordering policy with information updating, we also consider using blockchain technology for cold chain management in vaccine distribution. Indeed, the delivery of vaccines is another challenge faced by governments. Since the vaccines lose their efficacy rapidly at temperatures above 10℃, a tangled cold chain network of shipping, freezing, storage, and communication is required during the global delivery of vaccines. It is reported that up to 25% of vaccine doses are lost when supplying vaccines to rural healthcare centers and remote villages (Vesper, 2020). Thus, before ordering vaccines, governments must establish a reliable vaccine cold chain system with manufacturers and carefully measure their cold chain capacities. According to the WHO's report, the cold chain can help ensure that vaccines are stored and transported within recommended temperature ranges to keep the product quality from production to the last point of distribution (WHO, 2015). Under this circumstance, blockchain technology, which can provide transparent and trackable data, is considered to help improve cold chain performance and maintain the vaccine's efficacy by reducing temperature variation during shipment. For instance, IBM has adopted blockchain technology to support the vaccine distribution network to enhance the manufacturer's regulatory ability (e.g., quickly identifying potential threats in the vaccine supply chain), the distributor's real-time visibility (e.g., inventory visibility), and the public's trust in the vaccine (IBM News, 2020).

This study is mainly related to two research streams, namely, (i) vaccine supply chain management, and (ii) two-stage ordering with information updating. The vaccine supply chain has been getting increased attention in the past years, which consists of four aspects: "product (Wu et al. 2005, Robbins and Jacobson 2011, Robbins and Lunday 2016), production (Dai 2015, Arifoğlu and Tang 2021, Lin et al. 2022), allocation (Sun et al. 2009, Mamani et al. 2013), and distribution (Salmerón and Apte 2010, Yarmand et al. 2014)" (Duijzer et al., 2018). In the inventory/ordering problems, demand information updating has been studied for many decades (e.g., Dvoretzky et al. 1952, Scarf 1959). Much literature has accumulated since, as surveyed by Perera and Sethi (2023a,b). Since the information observed in the first stage can help update the demand distribution, researchers have realized the superiority of multi-stage ordering strategies (Sethi et al. 2001, 2003, 2005, Chen et al. 2010, Zhang et al. 2020, Chao et al. 2021).This study follows the extant literature to adopt Bayesian theory to depict the demand updating in vaccine ordering. While unlike the prior literature, this work integrates crucial characteristics of the vaccine supply chain (including vaccines' efficacy, the disease's infection rate, shipping time, cold chain requirement, etc.) into a two-stage two-ordering inventory model and pays attention to the performance of social welfare.

5.1.2 Research Questions and Contributions

Motivated by the above background and real-world challenges, we study a government's optimal dynamic ordering policy of COVID-19 vaccines. Specifically, we want to answer the following research questions:

(i) With information updating, what is the government's optimal dynamic vaccine ordering policy that would maximize social welfare? What is the best course of action for the government to take when there exists an alternative vaccine manufacturer in the market?

(ii) How do the critical factors (including the efficacy level of vaccines, disease's infection rate, shipping time, etc.) influence the government's optimal ordering decisions?

(iii) With real-world scenarios in mind, the following questions arise: (a) Can the use of blockchain technology help enhance the vaccine cold chain performance? How does it affect the government's decisions? (b) When considering the impacts of vaccine's side effects, how should the government make its ordering decisions?

To answer these critical research questions, we establish a two-stage two-ordering newsvendor model in a supply chain with Bayesian information updating and derive the optimal policy by using dynamic programming. In the basic model, we examine two cases when two different vaccines from the respective suppliers (A and B) have different efficacy levels. The government may order at both stages may change its first-stage vaccine supplier upon demand information updating. Following observed industrial practices (especially during the early stage of the pandemic), two cases raise: (i) the government orders vaccines from the same supplier at both stages (Case AA), and (ii) the government changes its supplier in the second stage (Case AB). We then extend our analyses to consider: (a) The use of blockchain technology to eliminate the negative impact of the long shipping time and (b) the exploration of the impacts of the vaccine's potential side effects.

Our analysis yields some insights. First, the government need not order vaccines as early as possible. When the disease's infection rate is low, the government should order nothing at the first stage and order only at the second stage with the updated demand information; and when it is high, the government should order at the first stage. More importantly, our results indicate that the government should select its vaccine supplier based on the disease's infection rate in the country/region. Specifically, when the infection rate is low, the government should change the supplier with a higher efficacy level in the second stage (compared with the one in the first stage) after information updating. When the infection rate is high, changing to the supplier with a lower efficacy level in the second stage is more advisable. When the infection rate is moderate, the government should order vaccines from the same supplier in both stages. This finding is consistent with the observed real-world practices that, in most cases, the governments decided to order from alternative vaccine suppliers during the most severe period of the COVID-19 pandemic when the infection rate was high (see Table 5-1).

In the extended models, our results uncover that the shipping time and the infection rate of COVID-19 will jointly affect the value of blockchain adoption in the vaccine cold chain. To be specific, the use of blockchain is recommended when (i) the shipping time is relatively long, or (ii) the government decides not to change its vaccine supplier after information updating (in a place with a high infection rate). Moreover, when considering the vaccine's side effects, the value of information updating is reduced as the government becomes less likely to order at the second stage. Additionally, for places with many older adults, the government should not change its vaccine supplier after information updating, as the social performance will suffer due to the side effects.

To our best knowledge, this is the first analytical study examining the government's dynamic vaccine ordering policy with demand information updating to maximize social welfare. We combine our findings with real-world practices to provide implications and suggestions to the government about selecting its vaccine supplier and the optimal ordering policy. The theoretical contribution of this study is integrating the critical features of vaccines (e.g., efficacy levels) into the two-stage ordering policy and evaluating the governing factors (e.g., the disease's infection rate, shipping time) that affect the government's optimal ordering decisions. Besides, we highlight the value of blockchain adoption in the vaccine cold chain and figure out the corresponding conditions that benefit the society regarding vaccine ordering.

5.2 Basic Model

We consider a two-stage two-ordering problem in a supply chain with Bayesian information updating. The supply chain consists of one government and two suppliers. The suppliers offer the vaccines at different time points, resembling the case when the COVID-19 pandemic just started. The efficacy levels of the vaccines provided by the two suppliers, A and B, are heterogeneous and denoted as e_A and e_B, respectively. e_A can be either larger or smaller than e_B. The parameter t refers to the shipping time of vaccine delivery, which only occurs when receiving the vaccines at the end of the planning horizon and is considered to capture the perishability of vaccines. Specifically, we consider the case that the vaccine will lose its efficacy (i.e., e_n, where $n = A$ or B) at probability $G(t) \in [0,1]$, which is a convex increasing function of t. That is, the vaccine's efficacy level is either e_n with probability $1 - G(t)$ or zero with probability $G(t)$. Moreover, the longer the shipping time is, the more likely the vaccine loses all of its efficacy. This setting is based on real-world practices. For instance, according to the official guidance provided by Ontario government in Canada, the vaccines exposed to unacceptable conditions will rapidly lose their efficacy (i.e., $e_n = 0$) and should be discarded[16]. In Bangladesh, it is reported that up to 25% of COVID-19 vaccine has lost its efficacy after being distributed to rural healthcare centers and remote villages with long shipping times (Vesper, 2020). The two suppliers sell their vaccines to the government at wholesale prices w_A and w_B. Usually, a higher efficacy level leads to a higher wholesale price; that is, when $e_A > e_B$, then $w_A > w_B$, and vice versa.

In our model, the number of people potentially interested in getting vaccinated (i.e., the potential "market size") is denoted by $\overline{m}$, which is a random variable following the normal distribution with a mean m and a variance δ^2. Here, the mean m is also unknown and follows a normal distribution:

[16] Vaccine Storage and Handling Guidelines: https://www.health.gov.on.ca/en/pro/programs/publichealth/oph_standards/docs/reference/vaccine%20_storage_handling_guidelines_en.pdf.

$m \sim Normal(\mu_1, d_1)$. The logic behind the assumption is that, the potential market size is a random variable in which the mean varies (which is also the most interesting thing to forecast). Still, there is a particular inherent uncertainty that cannot be reduced by whatever observations, i.e., the known variance. This modelling approach tells us that the expected value cannot truly represent the actual value, but the level of uncertainty can somehow be estimated. From statistics, we can treat the known variance as the variation of "demand" even at the start of the vaccine period, i.e., the number of people interested is still not precisely known and involves some variation. Therefore, the Bayesian conjugate pair with constant variance adopted in this study not only ensures the closed-form results can be derived, but it is also practical. In this paper, people's (called "consumers") utility consists of three parts: (i) The value of vaccination denoted by v. Following the mainstream literature (Feng et al., 2017; Yi et al., 2022), we model v to follow a uniform distribution with the support of [0,1]. An unvaccinated person always receives zero valuation. (ii) The hassle cost of vaccination (e.g., making an appointment), denoted by $\gamma(> 0)$, is incurred only when the person decides to go and get vaccinated. (iii) The disutility caused by the probability of infection.

We use r to represent the disease's infection rate. Then, the infection probability for individuals who do not get vaccinated is r, and it will be reduced to $r(1-(1-G(t))e_n)$ when the individual is vaccinated. This setting is consistent with the prior healthcare literature (Xu et al., 2022a). The rationale behind is: (i) Vaccinating with a higher efficacy level vaccine can lead to a lower infection probability for the individual; that is, the infection probability is decreasing in the vaccine efficacy. (ii) When there is no outbreak (i.e., $r = 0$), the infection probability always equals zero. (iii) When the vaccine's efficacy level is extremely low (i.e., $e_n = 0$), the infection probabilities for vaccinated and unvaccinated individuals are the same. Here, note that consumers can realize the vaccine distribution $G(t)$ through the information released by related authorities. For example, this kind of information is publicly available through the National Deployment and Vaccination Plan (NDVP), which is an operational plan for COVID-19 vaccines developed by countries to show the key information such as regulatory preparedness, supply chain, and health care waste management, vaccine safety, etc. (WHO, 2021). Based on the above considerations, we have the consumer utility for the one who does not go vaccinated as $-r$, and the consumer utility for the one who is vaccinated as $v-\gamma-r(1-(1-G(t))e_n)$, where $n = A$ or B. Consumers are self-interested, meaning that they will get vaccinated only when they can derive a higher utility from vaccination, i.e., $v-\gamma-r\big(1-\big(1-G(t)\big)e_n\big)>-r$. By rearranging terms, we have $v>\gamma-r(1-G(t))e_n$. Recall that v is uniformly distributed between $[0,1]$. Hence the fraction of consumers who want to vaccinate is realized as $1-\gamma+r(1-G(t))e_n$ (P.S.: Please see Figure 5-1 for consumer partitions). Then, scaled by the potential market size $\overline{m}$, we derive the (random) demand for vaccines in the market as $\overline{m}(1-\gamma+r(1-G(t))e_n)$.

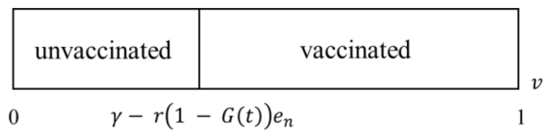

Figure 5-1. Consumer partitions of vaccination behavior.

In our two-stage problem, Suppliers A and B's efficacy levels are publicly available from WHO's website even before the vaccines are approved.[17] Thus, the government at Stage 1 will know the efficacy levels of vaccines of both Suppliers A and B. At Stage 1 (i.e., the time when the government needs to order q_1 from vaccine Supplier A to satisfy its lead time requirement), the government's forecast for the demand for the vaccine is $D_1|m\sim Normal(m\big(1-\gamma+r\big(1-G(t)\big)e_A\big),\delta)$. Since in our model, $m\sim Normal(\mu_1,d_1)$, the unconditional distribution of D_1 is given by $D_1\sim Normal(\mu_1\big(1-\gamma+r\big(1-G(t)\big)e_A\big),\sigma_1^2)$, where $\sigma_1^2\equiv\delta^2+(1-\gamma+r\big(1-G(t)\big)e_A)^2d_1^2$. From Stage 1 to Stage 2, i.e., between the ordering time points from Supplier A and the next order (who can be Supplier B or Supplier A again), with digital technologies, the government can observe the number of people who are interested in taking the vaccine and update the forecast. We call this observation ω. In the context of COVID-19 pandemic, the observation can be obtained via online questionnaires conducted by the government, which would help understand the people's potential interests in vaccination for the next stage. For instance, in the United States, the office of the Assistant Secretary for Planning and Evaluation (ASPE) conducted a Household Pulse Survey to investigate the people's COVID-19 vaccination intentions from April 2021 to January 2022 (Holtkamp et al., 2022). By using Bayesian conjugate pair theory (Choi et al., 2003), the distribution of m becomes

[17] See the "status of COVID-19 Vaccines within WHO EUL/PQ evaluation process", which is available at: https://www.who.int/teams/regulation-prequalification/eul/covid-19, date of access: 1 June 2021.

$m|\omega \sim Normal(\mu_2, d_2)$ with $\mu_2 = \frac{d_1\omega}{d_1+\delta} + \frac{\delta\mu_1}{d_1+\delta}$ and $d_2 = \frac{\delta d_1}{d_1+\delta}$, and the updated demand forecast for the vaccine in Stage 2 can be realized as D_2: $x_2 \equiv D_2|\mu_2 \sim Normal(\mu_2(1-\gamma+r(1-G(t))e_n), \sigma_2^2)$, where $\sigma_2^2 \equiv \delta^2 + (1-\gamma+r(1-G(t))e_n)^2 d_2^2$, and $n = A$ or B. The marginal distribution of μ_2 is $\mu_2 \sim Normal(\mu_1, \frac{d_1^2}{d_1+\delta})$. Then, in Stage 2, the government has an opportunity to add order and/or change the vaccine supplier with updated information, while having to bear an additional cost c for having a shorter lead time. Consequently, the government can have three choices for Stage 2 based on the updated demand information: (i) doing nothing, (ii) ordering q_2 units of vaccine from Supplier A (Case AA) with a price $w_A + c$, and (iii) ordering q_2 units of vaccine from Supplier B (Case AB) with a price $w_B + c$. The government's objectives in the two stages are the same, i.e., to maximize the social welfare, which will be discussed in detail later in subchapter 5.2.1. We do not consider the case when the government orders from Suppliers A and B simultaneously in this stage. The reasons are: (i) For tractability purposes, and (ii) this setting is in line with the real-world practices of the government's vaccine ordering policy (P.S.: See Table 5-1). After that, the orders arrive, and the vaccination period starts. The vaccine leftover at the end of the vaccination period incurs the unit holding cost $h > 0$ and the salvage value is zero. We consider that the holding cost is non-trivial in our study due to the strict storage conditions of vaccines, e.g., within specific temperature ranges. We show the sequence of the government's decisions in Figure 5-2.

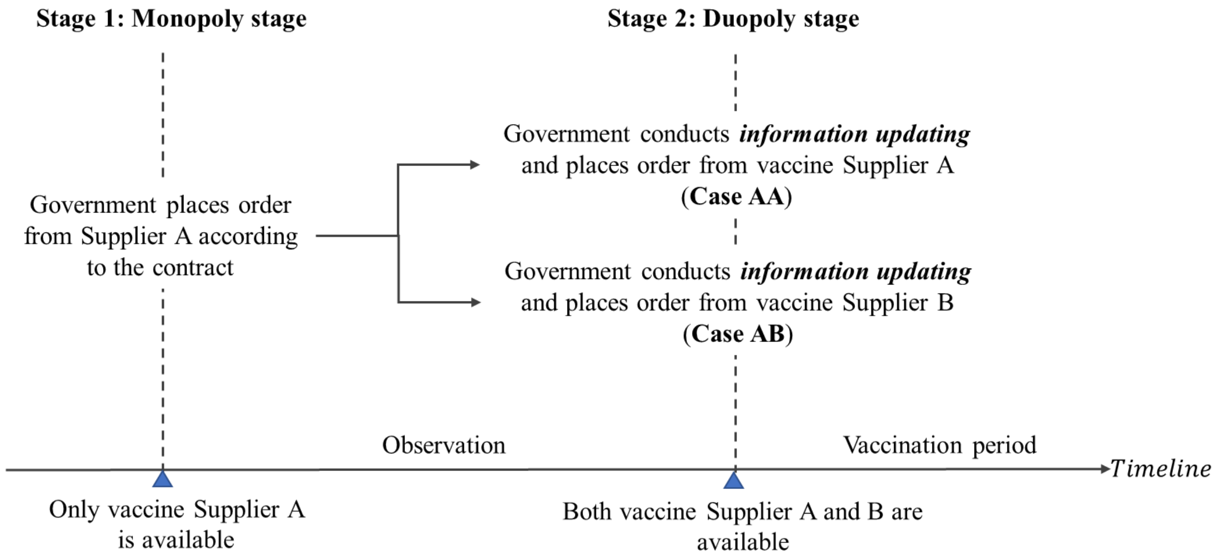

Figure 5-2. The sequence of decisions.

To improve presentation, we let $\varphi(\cdot)$ and $\Phi(\cdot)$ be the "standard normal density function" and "standard normal cumulative distribution function," respectively. We also present the inverse function of $\Phi(\cdot)$ by $\Phi^{-1}(\cdot)$, and the "right linear loss function of the standard normal distribution" is denoted by $\Psi(a) = \int_a^\infty (x-a)d\,\Phi(\cdot)$. We define $f(\cdot)$ as the probability density function of its argument.

5.2.1 Case AA: Ordering from Supplier A in Stage 2

In Case AA, we examine the government's vaccine ordering policy when it decides to order from the same supplier (i.e., Supplier A) after updating the demand information. Using backward induction, we first present the government's vaccine procurement cost and consumer surplus in Stage 2 in (1) and (2). Here, we follow Adida et al. (2013) to evaluate the consumer surplus, which refers to the total benefits received by all the vaccinated and unvaccinated people.

$$C_2^{AA} = E[(w_A + c)q_2 + h(q_1 + q_2 - D_2)^+] \tag{5.1}$$

$$CS_2^{AA} = E[\big(v - \gamma - r\big(1 - \big(1 - G(t)\big)e_A\big)\big)\min(D_2, q_1 + q_2) + (-r)(q_1 + q_2 - D_2)^-] \tag{5.2}$$

$$SW_2^{AA}(q_2|\mu_2, q_1) = CS_2^{AA} - C_2^{AA} \tag{5.3}$$

Since under the pandemic, social welfare should be prioritized when the government makes decisions (Ivanov and Dolgui 2020a, Xu et al. 2021), we set social welfare in (5.3) as the objective function of the government; it equals the consumer surplus minus the total cost. Note that the social welfare function used in our paper is not the same as the one in the traditional economic setup, which pays great attention to price and profit. In this study, we follow the mainstream OM literature related to vaccine supply chains (e.g., Deo and Corbett, 2009; Cho, 2010) to evaluate the social welfare from people and cost perspectives, ignoring the performance of a firm's profit. Particularly, the consumer surplus evaluated in our study can reflect the influence of infection transmission, which is one of the factors that the government most concerns about during the pandemic. Following Kaplan (2020), we define {The chance of infection transmission}={infection probability}×{number of people}. Then, as we can observe from the consumer surplus functions (e.g., $CS_2^{AA} = E[\big(v - \gamma - r\big(1 - \big(1 - G(t)\big)e_A\big)\big)\min(D, q_1 + q_2) + (-r)(q_1 + q_2 - D_2)^-]$), if more people are vaccinated (i.e., $\min(D, q_1 + q_2)$) is larger and ($(q_1 + q_2 - D_2)^-$ is smaller), the consumers are more benefited as the infection transmission is lower (i.e., $r\big(1 - \big(1 - G(t)\big)e_A\big)\min(D, q_1 + q_2) + r(q_1 + q_2 - D_2)^-$ is smaller). Therefore, we believe that the objective functions set in our model are reasonable.

We derive the optimal order quantity at Stage 2 under Case AA: $q_2^{AA*} = \max\{0, \mu_2[1-\gamma+r(1-G(t))e_A] + \sigma_2 \Phi^{-1}(s) - q_1\}$, where $s = \frac{1-2(\gamma+w_A+c-r(1-G(t))e_A)}{1+2(h-\gamma+r(1-G(t))e_A)}$ and s represents the inventory service level of the vaccine in Stage 2, which reflects the probability of not having a stock-out. Generally, a higher service level leads to a higher order quantity while may also result in a higher holding cost. The derivations of optimal decisions are available in Appendix B.

Proposition 5.1. *(i) When* $\mu_2 > \overline{\mu}^{AA}$*,we have* $q_2^{AA*} > 0$*; when* $\mu_2 \leq \overline{\mu}^{AA}$*, we have* $q_2^{AA*} = 0$*, where* $\overline{\mu}^{AA} = \frac{q_1 - \sigma_2 \Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_A}$*. (ii)* $\overline{\mu}^{AA}$ *is decreasing in* e_A *and* r*.*

Proposition 5.1 shows that the optimal order quantity in Stage 2 depends on μ_2 (random variable in Stage 1). Only when μ_2 is larger than a threshold, will the government make an order from Supplier A in Stage 2; otherwise, the government will order nothing. This finding is in line with the prior two-stage ordering studies (e.g., Choi et al., 2003; Zhang et al., 2020). Besides, we notice that the threshold can be influenced by the vaccine's efficacy level e_A and the infection rate r. To be specific, the government is more likely to make an order in Stage 2 either when the vaccine's efficacy level is higher, or the infection rate is larger. This finding is understandable as both the higher efficacy level and infection rate significantly increase the vaccine demand, which encourages the government to prepare more vaccines in Stage 2 to fulfill the demand.

We then bring the dynamic program back to Stage 1 and derive the benefit-to-go in Stage 1 as:

$$\begin{aligned} SW_1^{AA}(q_1|\mu_1) = &\int_{-\infty}^{\frac{q_1-\sigma_2\Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_A}} E[SW_2^{AA}(q_2^{AA*} = 0|\mu_2, q_1)] f(\mu_2) d\mu_2 \\ &+ \int_{\frac{q_1-\sigma_2\Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_A}}^{+\infty} E[SW_2^{AA}(q_2^{AA*} > 0|\mu_2, q_1)] f(\mu_2) d\mu_2 - w_A q_1. \end{aligned} \tag{5.4}$$

To enhance presentation, we let $K_A = \frac{1}{2} - \gamma - r[1-(1-G(t))e_A] + h + r$ and $m_A = \mu_2(1-\gamma+r(1-G(t))e_A)$. The closed-form expressions for $E[SW_2^{AA}(q_2^{AA*} = 0|\mu_2, q_1)]$ and $E[SW_2^{AA}(q_2^{AA*} > 0|\mu_2, q_1)]$ are:

$E[SW_2^{AA}(q_2^{AA*} = 0|\mu_2, q_1)]$

$$= \int_{-\infty}^{q_1} [v - \gamma - r(1 - (1 - G(t))e_A)] x_2 f(x_2) dx_2$$

$$+ \int_{q_1}^{\infty} [v - \gamma - r(1 - (1 - G(t))e_A)] q_1 f(x_2) dx_2 - \int_{q_1}^{\infty} r(x_2 - q_1) f(x_2) dx_2$$

$$+ \int_{-\infty}^{q_1} (-h)(q_1 - x_2) f(x_2) dx_2 = K_A \left[m_A - \sigma_2 \psi\left(\frac{q_1 - m_A}{\sigma_2}\right)\right] - r m_A - h q_1$$

$E[SW_2^{AA}(q_2^{AA*} > 0|\mu_2, q_1)]$

$$= \int_{-\infty}^{m_A + \sigma_2 \Phi^{-1}(s)} [v - \gamma - r(1 - (1 - G(t))e_A)] x_2 f(x_2) dx_2$$

$$+ \int_{m_A + \sigma_2 \Phi^{-1}(s)}^{\infty} [v - \gamma - r(1 - (1 - G(t))e_A)](m_A + \sigma_2 \Phi^{-1}(s)) f(x_2) dx_2$$

$$- \int_{m_A + \sigma_2 \Phi^{-1}(s)}^{\infty} r(x_2 - m_A - \sigma_2 \Phi^{-1}(s)) f(x_2) dx_2$$

$$+ \int_{-\infty}^{m_A + \sigma_2 \Phi^{-1}(s)} (-h)(m_A + \sigma_2 \Phi^{-1}(s) - x_2) f(x_2) dx_2 - (w_A + c)[m_A + \sigma_2 \Phi^{-1}(s)$$

$$- q_1]$$

$$= (K_A - r) m_A - (h + w_A + c)[m_A + \sigma_2 \Phi^{-1}(s)] - K_A \sigma_2 \psi(\Phi^{-1}(s)) + (w_A + c) q_1$$

Based on the above expected benefit-to-go functions in Stage 1, we derive the optimal order quantity in Stage 1 (q_1) for the government by maximizing $SW_1^{AA}(q_1|\mu_1)$. We define:

$z_A = \frac{q_0 - \sigma_2 \Phi^{-1}(s)}{1 - \gamma + r(1 - G(t))e_A}$,

$\lambda = \frac{\mu_2 - \mu_1}{\sqrt{d_1^2/(d_1 + \delta)}}$, and

$$X(q_1)^{AA} = -K_A \int_{-\infty}^{\frac{z_A - \mu_1}{\sqrt{d_1^2/(d_1+\delta)}}} \left[\Phi\left(\frac{q_1 - (1 - \gamma + r(1 - G(t))e_A)\left(\sqrt{d_1^2/(d_1+\delta)}\lambda + \mu_1\right)}{\sigma_2}\right)\right] \varphi(\lambda) d\lambda + (K_A - h - w_A - c)\Phi\left(\frac{z_A - \mu_1}{\sqrt{d_1^2/(d_1+\delta)}}\right) + c.$$

Lemma 5.1. *(i) The expected benefit-to-go in Stage 1, $SW_1^{AA}(q_1|\mu_1)$ is a strictly concave function of q_1. (ii) The optimal order quantity in Stage 1, q_1^{AA*}, can be uniquely determined as follows: if $r >$*

$\frac{\gamma+w_A+c-\frac{1}{2}-c/\Phi\left(\frac{z_A-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}\right)}{(1-G(t))e_A}$, *then* $q_1^{AA*} = \max\{0, \arg_{q_1}\{X(q_1)^{AA} = 0\}\}$; *while if* $r \le \frac{\gamma+w_A+c-\frac{1}{2}-c/\Phi\left(\frac{z_A-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}\right)}{(1-G(t))e_A}$, *then* $q_1^{AA*} = 0$.

Lemma 5.1 proves the existence of the optimal order quantity in Stage 1. The result shows that when the disease's infection rate is higher than a threshold, the government will order the vaccine in Stage 1; otherwise, the government will postpone all the orders until Stage 2 after demand information updating. Conventional wisdom suggests that the government should order vaccines as early as possible. However, in fact, a low disease's infection rate will cause a demand reduction which deters the government from early purchasing of vaccines. Under this circumstance, we suggest the government fully use the information updating and only order vaccines in Stage 2.

5.2.2 Case AB: Ordering from Supplier B in Stage 2

In Case AB, the government will change its vaccine supplier from Supplier A to Supplier B after demand information updating. Both the scenarios when $e_A > e_B$ and $e_A \le e_B$ are examined. Similar to Case AA, the government makes its optimal ordering decisions to maximize social welfare, as shown in (5.7).

$$C_2^{AB} = E[(w_B + c)q_2 + h(q_1 + q_2 - D_2)^+] \tag{5.5}$$

$$CS_2^{AB} = \begin{cases} E\begin{bmatrix} \left(v-\gamma-r\left(1-(1-G(t))e_A\right)\right)\min(D_2, q_1) + \\ \left(v-\gamma-r\left(1-(1-G(t))e_B\right)\right)\min((D_2-q_1)^+, q_2) - r(q_1+q_2-D_2)^- \end{bmatrix} & if\ e_A > e_B \\ E\begin{bmatrix} \left(v-\gamma-r\left(1-(1-G(t))e_A\right)\right)\min((D_2-q_2)^+, q_1) + \\ \left(v-\gamma-r\left(1-(1-G(t))e_B\right)\right)\min(D_2, q_2) - r(q_1+q_2-D_2)^- \end{bmatrix} & if\ e_A \le e_B \end{cases}$$

(5.6)

$$SW_2^{AB}(q_2|\mu_2, q_1) = CS_2^{AB} - C_2^{AB} \tag{5.7}$$

We derive the optimal ordering quantity in Stage 2 under Case AB: $q_2^{AB*} = \max\{0, \mu_2[1-\gamma+r(1-G(t))e_n] + \sigma_2\Phi^{-1}(s) - q_1\}$, where $n = \begin{cases} A, & if\ e_A > e_B \\ B, & if\ e_A \le e_B \end{cases}$, $s = \begin{cases} \frac{1-2(\gamma+w_B+c-r(1-G(t))e_B)}{1+2(h-\gamma+r(1-G(t))e_B)}, & if\ e_A > e_B \\ \frac{1-2(\gamma+w_B+c-r(1-G(t))e_B)}{1+2(h-\gamma+r(1-G(t))e_A)}, & if\ e_A \le e_B \end{cases}$, and s represents the inventory service level of the vaccine in Stage 2. The derivations of optimal decisions are available in Appendix B.

Proposition 5.2. *(i) When* $\mu_2 > \overline{\mu}^{AB}$*,we have* $q_2^{AB*} > 0$*; when* $\mu_2 \leq \overline{\mu}^{AB}$*, we have* $q_2^{AB*} = 0$*, where* $\overline{\mu}^{AB} = \frac{q_0 - \sigma_2 \Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_n}$*. (ii) If* $e_A > e_B$*,* $\overline{\mu}^{AB}$ *is decreasing in* e_A *and* e_B*; while if* $e_A \leq e_B$*,* $\overline{\mu}^{AB}$ *is increasing in* e_A *and decreasing in* e_B*.*

Proposition 5.2(i) shows similar results as the ones under Case AA: The government will place an order from Supplier B in Stage 2 only when μ_2 is larger than a threshold; otherwise, the government will order nothing. From Proposition 5.2(ii), we find that a higher efficacy level does not necessarily result in a higher order quantity in Stage 2. Specifically, with an increase of Supplier A's vaccine efficacy level, the government is less likely to place an order from Supplier B in Stage 2 if Supplier B's vaccine efficacy level is higher than Supplier A's. In other words, it is unwise for Supplier B to blindly increase its vaccine's efficacy level because the government is less willing to purchase from Supplier B when the vaccine's efficacy levels of both Suppliers A and B are sufficiently high. This finding is different from the result in Case AA. We hence suggest the government and suppliers make decisions carefully when facing competing vaccines in the market.

Next, similar to Case AA, we carry out the dynamic program back to Stage 1 and derive the benefit-to-go in Stage 1 for Case AB as follows:

$$SW_1^{AB}(q_1|\mu_1) = \int_{-\infty}^{\frac{q_1-\sigma_2\Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_n}} E[SW_2^{AB}(q_2^{AB*} = 0|\mu_2, q_1)]f(\mu_2)d\mu_2 + \int_{\frac{q_1-\sigma_2\Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_n}}^{+\infty} E[SW_2^{AB}(q_2^{AB*} > 0|\mu_2, q_1)]f(\mu_2)d\mu_2 - w_A q_1. \quad (5.8)$$

Recall that $K_A = \frac{1}{2} - \gamma - r[1 - (1 - G(t))e_A] + h + r$ and $m_A = \mu_2(1 - \gamma + r(1 - G(t))e_A)$. We then let $K_B = \frac{1}{2} - \gamma - r[1 - (1 - G(t))e_B]$ and $m_B = \mu_2(1 - \gamma + r(1 - G(t))e_B)$. The respective closed-form expressions for $E[SW_2^{AB}(q_2^{AB*} = 0|\mu_2, q_1)]$ and $E[SW_2^{AB}(q_2^{AB*} > 0|\mu_2, q_1)]$ are:

$$E[SW_2^{AB}(q_2^{AB*} = 0|\mu_2, q_1)] = E[SW_2^{AA}(q_2^{AA*} = 0|\mu_2, q_1)]$$
$$= K_A\left[m_A - \sigma_2\psi\left(\frac{q_1 - m_A}{\sigma_2}\right)\right] - rm_A - hq_1, \text{ and}$$

If $e_A > e_B$,

$$E[SW_2^{AB}(q_2^{AB*} > 0|\mu_2, q_1)]$$

$$= \int_{-\infty}^{q_1} [v - \gamma - r(1 - (1 - G(t))e_A)] x_2 f(x_2) dx_2$$

$$+ \int_{q_1}^{\infty} [v - \gamma - r(1 - (1 - G(t))e_A)] q_1 f(x_2) dx_2$$

$$+ \int_{-\infty}^{m_A + \sigma_2 \Phi^{-1}(s)} [v - \gamma - r(1 - (1 - G(t))e_B)] (x_2 - q_1) f(x_2) dx_2$$

$$+ \int_{m_A + \sigma_2 \Phi^{-1}(s)}^{\infty} [v - \gamma - r(1 - (1 - G(t))e_B)] q_2 f(x_2) dx_2$$

$$- \int_{m_A + \sigma_2 \Phi^{-1}(s)}^{\infty} r(x_2 - m_A - \sigma_2 \Phi^{-1}(s)) f(x_2) dx_2$$

$$+ \int_{-\infty}^{m_A + \sigma_2 \Phi^{-1}(s)} (-h)(m_A + \sigma_2 \Phi^{-1}(s) - x_2) f(x_2) dx_2 - (w_B + c)[m_A + \sigma_2 \Phi^{-1}(s) - q_1]$$

$$= (K_A - h - r)\left[m_A - \sigma_2 \psi\left(\frac{q_1 - m_A}{\sigma_2}\right)\right] + (K_B - h - r - w_B - c)(m_A - q_1)$$

$$- K_B \sigma_2 \psi(\Phi^{-1}(s)) - (h + w_B + c)\sigma_2 \Phi^{-1}(s)$$

while if $e_A \le e_B$,

$$E[SW_2^{AB}(q_2^{AB*} > 0|\mu_2, q_1)]$$

$$= \int_{-\infty}^{m_B + \sigma_2 \Phi^{-1}(s)} [v - \gamma - r(1 - (1 - G(t))e_A)] (x_2 - q_2) f(x_2) dx_2$$

$$+ \int_{m_B + \sigma_2 \Phi^{-1}(s)}^{\infty} [v - \gamma - r(1 - (1 - G(t))e_A)] q_1 f(x_2) dx_2$$

$$+ \int_{-\infty}^{m_B + \sigma_2 \Phi^{-1}(s)} [v - \gamma - r(1 - (1 - G(t))e_B)] x_2 f(x_2) dx_2$$

$$+ \int_{m_B + \sigma_2 \Phi^{-1}(s)}^{\infty} [v - \gamma - r(1 - (1 - G(t))e_B)] q_2 f(x_2) dx_2$$

$$- \int_{m_B + \sigma_2 \Phi^{-1}(s)}^{\infty} r(x_2 - m_B - \sigma_2 \Phi^{-1}(s)) f(x_2) dx_2$$

$$+ \int_{-\infty}^{m_B + \sigma_2 \Phi^{-1}(s)} (-h)(m_B + \sigma_2 \Phi^{-1}(s) - x_2) f(x_2) dx_2 - (w_B + c)[m_B + \sigma_2 \Phi^{-1}(s) - q_1$$

$$= (K_A - h - r)\left[q_1 - \sigma_2\Phi^{-1}(s) - \sigma_2\psi\left(\Phi^{-1}(s)\right)\right] + (K_B - h - r)\left[m_B - \sigma_2\psi\left(\frac{\sigma_2\Phi^{-1}(s) - q_1}{\sigma_2}\right)\right]$$

$$- (h + r)\sigma_2\psi\left(\Phi^{-1}(s)\right) - (h + w_B + c)\sigma_2\Phi^{-1}(s) - (m_B - q_1)(w_B + c)$$

We let $\bar{r} = \frac{w_A - w_B}{(1-G(t))(e_A - e_B)}$. The expressions of $\bar{h}$ and $X(q_1)^{AB}$ can be found in Appendix B.

Lemma 5.2. *(i) The expected benefit-to-go in Stage 1, $SW_1^{AB}(q_1|\mu_1)$ is a concave function of q_1 if and only if $h > \bar{h}$. (ii) The optimal order quantity in Stage 1, q_1^{AB*}, can be uniquely determined as follows: if $r > \bar{r}$, then $q_1^{AB*} = \max\{0, \arg_{q_1}\{X(q_1)^{AB} = 0\}\}$; while if $r \leq \bar{r}$, then $q_1^{AB*} = 0$.*

We argue that the holding cost condition in Lemma 5.2(i) is naturally satisfied in the real world. As introduced above, the cold chain requirement for vaccine storage is extremely strict (especially on temperature control), which results in a high holding cost in practice. Additionally, Lemma 5.2(ii) uncovers that when the disease's infection rate is relatively low, there's no need for the government to order vaccines in Stage 1 with high market uncertainty. This finding is the same as the one obtained in Case AA.

We summarize the optimal ordering policy for the government in Theorem 5.1.

Theorem 5.1. *In Stage 1, determine q_1^{AA*} (or q_1^{AB*}) by checking the decision rule proposed in Lemma 5.1 (or Lemma 5.2). In Stage 2, after observation and information updating, μ_2 can be realized; then, q_2^{AA*} (or q_2^{AB*}) can be decided as $q_2^{AA*} = \max\{0, \mu_2[1 - \gamma + r(1 - G(t))e_A] + \sigma_2\Phi^{-1}(s) - q_1\}$ (or $q_2^{AB*} = \max\{0, \mu_2[1 - \gamma + r(1 - G(t))e_n] + \sigma_2\Phi^{-1}(s) - q_1\}$, where $n = \begin{cases} A, & if\ e_A > e_B \\ B, & if\ e_A \leq e_B \end{cases}$).*

5.3 Decision Analyses

In Chapter 5.2, we have analytically derived the government's optimal two-stage vaccine ordering decisions with information updating. In this chapter, we further analyze and demonstrate how the government's ordering decisions and social performance will be affected by different factors. Particularly, we will provide guidance on optimal ordering policy and vaccine supplier selection to the government.

5.3.1 Sensitivity analysis on ordering decisions

First, we discuss the impacts of crucial factors (e.g., disease's infection rate, vaccines' efficacy levels, shipping time, etc.) on the government's ordering decisions. Due to the difficulty in closed-form analysis, we conduct numerical studies and derive findings as follows. All the data we set follow the model assumptions (e.g., $G(t) \in [0,1]$, when $e_A > e_B$, then $w_A > w_B$, and vice versa.) and can help show the effects clearly. The detailed numerical settings and the corresponding Figures A5-1 to A5-7 are in Appendix A.

Observation 5.1. *(i) In Case AA, the government's optimal order quantity in Stage 1* q_1^{AA*} *is increasing in* e_A *and* r*, and decreasing in* t*. (ii) In Case AB, the government's optimal order quantity in Stage 1* q_1^{AB*} *is increasing in* e_A *and* r *and decreasing in* e_B *and* t*.*

Observation 5.1 gives a clear picture of the government's optimal ordering policy concerning the infection rate (r), the vaccines' efficacy levels (e_A, e_B), and the shipping time of the vaccine (t) in different cases. The results indicate that the government will always order more vaccines from Supplier A in Stage 1 to match the high potential demand if Supplier A's (Supplier B's) vaccine efficacy level is higher (lower) or the infection rate is higher. This result is understandable, as individuals tend to vaccinate if the infection rate is high, or the vaccine with a higher efficacy level should be more popular. Besides, the longer shipping time will reduce the government's ordering willingness because the vaccine's efficacy level will be decreased. Thus, it is critically important for the government to take measures (e.g., adopting blockchain technology) to eliminate such negative impact brought by the shipping time. The value of blockchain adoption in vaccine ordering will be further examined in the extended model in Chapter 5.4.1.

5.3.2 Sensitivity analysis on social performance

Next, to guide the government's optimal supplier selection decision, we conduct a sensitivity analysis for social welfare under Cases AA and AB. The numerical settings and corresponding figures can be checked in Figures A5-8 to A5-14 in Appendix A.

Observation 5.2. *(i) In Case AA, the optimal expected social welfare* SW_1^{AA*} *is concave in* r*, increasing in* e_A *and decreasing in* t*. (ii) In Case AB, the optimal expected social welfare* SW_1^{AB*} *is increasing in* r *and* e_A *and decreasing in* e_B*, if* $e_A > e_B$*, and decreasing in* r *and* e_B *and increasing in* e_A*, if* $e_A \le e_B$*.*

Observation 5.2 presents how the infection rate (r), the vaccines' efficacy levels (e_A, e_B), and the shipping time (t) can impact social welfare. First, notice that no matter in Case AA or AB, social welfare is increasing in Supplier A's vaccine efficacy level, and decreasing in both Supplier B's vaccine efficacy level and the shipping time. The main reason is on the ordering quantity. The government will reduce its order quantity when Supplier A's (Supplier B's) vaccine efficacy level is lower (higher) and the shipping time is longer (see Observation 5.1). These all harm the consumers and social welfare.

Then, regarding the influence of infection rate, we interestingly find that even though a higher infection rate (r) can induce a higher potential demand and a larger order quantity, it does not necessarily benefit social welfare in both Cases AA and AB. Specifically, if the government does not change its supplier in Stage 2 (i.e., Case AA), the maximum social welfare can be achieved only when the infection rate is moderate. The reasons are: (i) When the infection rate is sufficiently low, fewer consumers are willing to vaccinate, which increases the infection probability and eventually harms the consumer surplus and social welfare; and (ii) when the infection rate is sufficiently large, vaccination is less efficient to reduce the potential harm brought by the virus to consumers, which results in a smaller social welfare. This finding implies that the optimal social welfare is concave in the infection rate. Hence, there exists a unique infection rate that maximizes the social welfare under a given vaccine efficacy level. In other words, the value of vaccine can be maximized by a "critical infection rate", rather than a higher one. According to Abedi et al. (2021), the infection rate per one million of COVID-19 ranges from 15.36 to 5093.99 in different counties. To guide the government on how to select a proper vaccine supplier based on its country's infection rate, we conduct numerical studies and summarize the results in Table A5-1 in Appendix A. It shows how vaccines with different efficacy levels can maximize social welfare under different infection rate ranges. Specifically, a high efficacy level is optimal for the place with a high infection rate and a low efficacy level is suitable to the place with a low infection rate. If the government decides to change its supplier in Stage 2 (i.e., Case AB), the government should (i) choose the vaccine Supplier B with a lower efficacy level (compared with Supplier A) when the infection rate is relatively high, and (ii) select the vaccine Supplier B with a higher efficacy level (compared with Supplier A) when the infection rate is relatively low. This finding is interesting as it means that after information updating, the high efficacy level of Supplier B is not always efficient to combat the high infection rate challenge. The sensitivity analysis results are summarized in Table 5-2.

Table 5-2. Summary of sensitivity analyses.

Sensitivity analysis for q_1^*				
	r	e_A	e_B	t
Case AA	↑	↑	N/A	↓
Case AB			↓	
Sensitivity analysis for SW_1^*				
	r	e_A	e_B	t
Case AA	↑ ↓	↑	N/A	↓
Case AB (if $e_A > e_B$)	↑		↓	
Case AB (if $e_A \le e_B$)	↓			

Remarks: " ↑ " means that an increase in the parameter leads to a larger q_1^* or SW_1^*; " ↓ " means that an increase in the parameter leads to a smaller q_1^* or SW_1^*; "N/A" means that q_1^* or SW_1^* is independent of the parameter.

5.3.3 Comparison results between Case AA and Case AB

To figure out the government's optimal vaccine selection decision in Stage 2, we compare the results derived in Cases AA and AB. We let $\bar{w}_A = \arg_{w_A}\{\frac{1-2\{\gamma+w_A-r[1-G(t)]e_A\}}{1+2\{h-\gamma+r[1-G(t)]e_A\}} = \frac{1-2\{\gamma+w_B-r[1-G(t)]e_B\}}{1+2\{h-\gamma+r[1-G(t)]e_B\}}\}$ and

$$\bar{\mu}_2 = \max\{0, \frac{\sigma_2\left\{\Phi^{-1}\left[\frac{1-2[\gamma+w_A-r[1-G(t)]e_A]}{1+2[h-\gamma+r[1-G(t)]e_A]}\right]-\Phi^{-1}\left[\frac{1-2[\gamma+w_B-r[1-G(t)]e_B]}{1+2[h-\gamma+r[1-G(t)]e_B]}\right]\right\}}{r[1-G(t)](e_B-e_A)}\}.$$

Proposition 5.3. *For given q_1, if $e_A > e_B$, then $q_2^{AA*} < q_2^{AB*}$ if and only if $w_A > \bar{w}_A$; while if $e_A \le e_B$, then $q_2^{AA*} < q_2^{AB*}$ if and only if $\mu_2 > \bar{\mu}_2$.*

Proposition 5.3 shows the comparison results for the ordering policies in Stage 2 between Cases AA and AB. The results imply that no matter whether Supplier B's vaccine efficacy level is high or low, if the government would order from Supplier B at Stage 2, she would order more vaccines than under Case AA in Stage 2. Specifically, if Supplier B's vaccine efficacy level is lower than Supplier A's, the government will order more from Supplier B when the wholesale price of Supplier A's vaccine is relatively large. This finding is logical as the high wholesale price will reduce the government's willingness to order. However, if Supplier B's vaccine efficacy level is higher than Supplier A's, the government should order more vaccines from Supplier B than Supplier A in Stage 2 when the market size is relatively large. The reason is that a higher efficacy level encourages more consumers to vaccinate, especially when the market size is huge, which prompts the government to order more vaccines to meet the demand. To summarize, the government's dynamic ordering decision is subtle. It depends on many crucial factors, including the vaccines' efficacy levels, the wholesale price, and the potential market size. The government should carefully make decisions based on our proposed findings.

Observation 5.3. *(i) When $e_A > e_B$, social welfare is higher in Case AA if r is relatively small; otherwise, social welfare is higher in Case AB. (ii) When $e_A \leq e_B$, social welfare is higher in Case AA if r is relatively large; otherwise, social welfare is higher in Case AB.*

Observation 5.3 guides the government's vaccine selection decision under the pandemic. Details of the numerical settings can be found in Figure A5-15 in Appendix A. The results show that it can be wise for the government to change its supplier (from Supplier A to Supplier B) after information updating, no matter the disease's infection rate is sufficiently low or high. However, the government should carefully investigate Supplier B's vaccine efficacy level before making decisions. When the infection rate is sufficiently low, only Supplier B with higher efficacy level (compared with Supplier A) is preferred in Stage 2; while when the infection rate is relatively large, Supplier B with a lower efficacy level (compared with Supplier A) is recommended. This finding is consistent with the real-world practices that many governments choose to order from different vaccine suppliers during the COVID-19 pandemic. Significantly, under the most challenging situation of COVID-19 with a high infection rate, places like the U.S., Europe, Hong Kong, and Japan decided to supplement their initial vaccine ordering from an alternative supplier with a relatively low efficacy level (See Table 5-1). However, when the disease's infection rate is moderate, our results suggest the government make an order from the same vaccine supplier with a moderate efficacy level at both stages. This finding is essential. It means that for those places with a moderate infection rate, it is unnecessary for the government to order vaccines from different suppliers; otherwise, social welfare will be harmed.

To provide helpful guidance for the government regarding its vaccine ordering policy, we depict Figure 5-3 to summarize all the essential findings including both the numerical and analytical ones) in the basic model. As shown in the figure, both the government's vaccine supplier selection and vaccine ordering decisions rely on the disease's infection rate. For example, when the infection rate is extremely high, the government should order vaccines from Supplier A at Stage 1 (P.S.: refer to Lemmas 5.1 and 5.2), and then change to Supplier B at Stage 2 if Supplier B's vaccine efficacy level is lower than Supplier A's; otherwise, the government should continue to order from Supplier A at Stage 2 (P.S.: refer to Observation 5.3). Similarly, when the infection rate is extremely low, the government should order nothing from Supplier A at Stage 1 and order from Supplier B at Stage 2 if

Supplier B's vaccine efficacy level is higher than Supplier A's; otherwise, the government should choose Supplier A at Stage 2. Besides, we conduct a sensitivity analysis for these thresholds (i.e., $\tilde{r}$, $\dot{r}$, and $\ddot{r}$) with respect to the shipping time t (P.S.: Proofs are in Appendix B). When the shipping time is longer, the government is more recommended to (i) postpone its ordering to the second stage (i.e., $\tilde{r}$ is increasing in t), and (ii) choose the alternative vaccine supplier (Supplier B) (i.e., $\dot{r}$ is increasing in t and $\ddot{r}$ is decreasing in t). This is because a longer shipping time leads to a lower vaccine demand (due to the loss of vaccine efficacy), which encourages the government to order less in the first stage and may choose an alternative supplier in the second stage to benefit consumers.

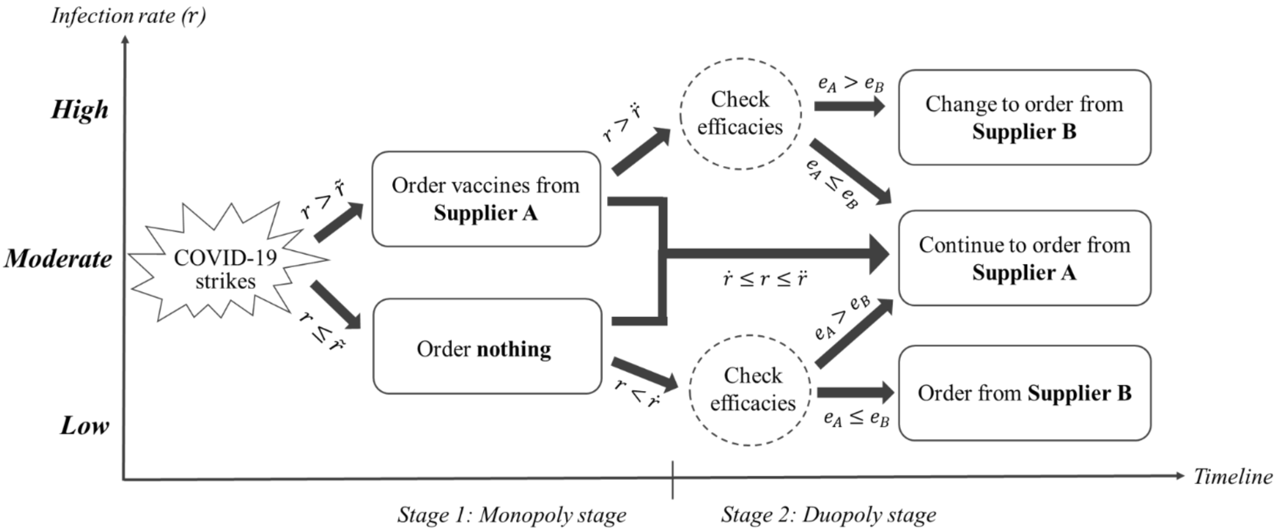

Figure 5-3. The government's optimal vaccine ordering policy under the pandemic (Remarks: $\tilde{r}$ and $\dot{r}$ are increasing in the shipping time t; $\ddot{r}$ is decreasing in t).

5.4 Extended Analyses

5.4.2 Ordering policy with blockchain adoption

As we have found in the basic model, a longer shipping time t increases the probability of losing vaccine efficacy $G(t)$ which decreases social welfare (P.S.: See Table 5-2). To address this challenge in cold chain management, blockchain technology is considered, as it can facilitate monitoring by enhancing data visibility and traceability (Yang et al., 2019; Hastig and Sodhi, 2020). IBM, one of the world's largest technology corporations, has established a blockchain system to support vaccine delivery during the pandemic. It claims that the blockchain component can help monitor and get the refrigerated containers' temperature data every 5 minutes, which ensures that the vaccines are all in good conditions without losing efficacy in the delivery process (IBM Garage, 2021). Hence, the role of blockchain adoption is to maintain cold-chain requirements and keep vaccine efficacy in vaccine ordering, which can help foster consumer confidence in vaccination.

In this subchapter, we consider the case where the government adopts blockchain technology to monitor the vaccine's shipping process. In our model settings, the value of blockchain adoption is shown by having $G(t) = 0$. In other words, with the use of blockchain, no matter the shipping time is long or short, the probability of losing vaccine's efficacy equals zero. Therefore, the value of blockchain is to eliminate the negative impacts brought by t instead of working on t directly. Then, the vaccinated consumer utility is given by $v - \gamma - r(1 - e_n)$, which is larger than the "without blockchain" case. However, the government should bear the nontrivial costs of blockchain implementation. It usually incurs two types of costs: a unit operations cost b and a fixed implementation cost F . The government should pay the unit operations cost for each quantity at two stages, and the fixed implementation cost is a lump sum paid in Stage 1. We use the superscript "BT" to denote the case with blockchain adoption. By using the same approach as the one in the basic model, we yield the optimal order quantities in two stages in the two cases. To save space in the mainbody, the optimal solutions and corresponding proofs for Cases AA and AB under blockchain adoption can be found in Appendix B. Here, we mainly present the analyses including comparisons between the blockchain adoption case and basic model as well as the value of blockchain adoption. We first compare the optimal order quantities between the blockchain adoption case (i.e., $q_k^{BT,AA*}$ in Case AA for $k = (1,2)$) and basic model in Proposition 5.4. All the proofs can be found in Appendix B.

Proposition 5.4. *(i) We have* $q_1^{BT,AA*} > q_1^{AA*}$. *(ii)For given* q_1, *we have* $q_2^{BT,AA*} > q_2^{AA*}$ *if and only if* $G(t) > \frac{\sigma_2[\Phi^{-1}(s) - \Phi^{-1}(s^{BT})]}{\mu_2 r e_A}$, *otherwise,* $q_2^{BT,AA*} \leq q_2^{AA*}$.

Proposition 5.4 shows the impact of blockchain adoption on the government's optimal ordering quantities. We find that the use of blockchain technology will always induce an increased vaccine ordering quantity in Stage 1, regardless of the shipping time. This finding verifies the significant contribution of blockchain adoption on eliminating the negative impact brought by the long shipping time. However, when it comes to Stage 2, we surprisingly notice that the use of blockchain technology does not necessarily lead to a higher order quantity, especially when the shipping time is relatively short. It means that when the market demand is updated, blockchain adoption becomes less useful.

We define $\Delta SW_1^i = SW_1^{BT,i}(q_1|\mu_1) - SW_1^i(q_1|\mu_1)$ as the value of blockchain adoption in terms of social welfare, where $i = AA$ or AB. We then conduct numerical analysis and yield Observation 5.4. Two different cases regarding the shipping time are examined, i.e., the case when t is small ($t = 0.5$) and the case when t is large ($t = 1$). More detailed numerical settings and the corresponding figure (i.e., Figure A5-16) are shown in Appendix A.

Observation 5.4. *(i) When the shipping time t is relatively small, blockchain adoption can only benefit social welfare in Case AA (i.e., $\Delta SW_1^{AA} > 0$) if the disease's infection rate (i.e., r) is relatively large; in Case AB, it always harms social welfare (i.e., $\Delta SW_1^{AA} < 0$) regardless of the infection rate.*
(ii) When the shipping time t is relatively large, blockchain adoption can always benefit social welfare in both Cases AA and AB.
(iii) The value of blockchain adoption increases in the infection rate r in Case AA while it decreases in the infection rate in Case AB.

Observation 5.4 presents the value of blockchain adoption in different cases. The results in Observations 5.4(i) and (ii) show whether the use of blockchain technology benefits social welfare depends on both the shipping time and the disease's infection rate. Specifically, blockchain adoption can always improve social welfare when the shipping time is relatively long. However, if the shipping time is relatively short, it never enhances social welfare in Case AB but could be effective in Case AA as long as the disease's infection rate is relatively high. This finding gives two implications: (i) The value of blockchain adoption is increasing with the shipping time, which is logical as it can eliminate the negative impact of shipping time on the vaccine efficacy; (ii) blockchain adoption is valuable for the highly infectious disease if the government does not change its vaccine supplier in Stage 2 (i.e., Case AA). Moreover, we interestingly notice that if the government decides to change the supplier in Stage 2 (i.e., Case AB), blockchain adoption is harmful to social welfare under the high infectious disease scenario. The potential reason can be twofold: First, as we have found in Proposition 5.4, the blockchain adoption is less efficient after information updating, which results in a lower order quantity in Stage 2 that harms social welfare. Second, a higher infection rate will lead to a higher ordering cost for the government, which also harms social welfare. To summarize, blockchain adoption is more recommended to the place with high (low) infection rate if the government decides not to change (decides to change) its vaccine supplier in Stage 2.

5.4.2 Ordering policy with side effects

In this subchapter, we check the robustness of our study by considering the vaccine's side effects. We use the superscript "SE" to denote this case. This consideration is based on real-world observations that the COVID-19 vaccine's side effects will significantly influence the government's vaccine-ordering decisions as it affects the individuals' willingness to be vaccinated. As reported by Nguyen et al. (2021), concerns about side effects are the major reason why individuals do not intend to get vaccinated for COVID-19. For instance, the U.S. Centres for Disease Control and Prevention has suspended the injection of Johnson & Johnson's COVID-19 vaccine, as a severe side effect (e.g., a blood-clotting disorder) is reported. Similarly, a significant number of European countries (including Italy, Germany, France, Denmark, Spain, etc.) have called for a pause in the use of AstraZeneca's COVID-19 vaccine because of the potential side effects of blood clots (McCarthy, 2021).

Based on the above consideration, we follow real-word cases and consider that the vaccine's side effects $\xi_{n,j}$ will negatively impact consumer utility. The side effect varies in different age groups, where $n = A$ or B denotes the vaccine from different suppliers, and j represents different age groups. We follow Riad et al. (2021) and identify two age groups, i.e., ≤ 45 years old (youth, $j = y$) and > 45 years old (elder, $j = e$). As revealed by Riad et al. (2021), the vaccine's side effect is more prevalent among the youth group than the elder group, i.e., $\xi_{n,y} > \xi_{n,e}$. The population proportion of each group is denoted by α_j, where $\alpha_y + \alpha_e = 1$. Hence, in this case, we let $L_n = \alpha_y \xi_{n,y} + \alpha_e \xi_{n,e}$ and have the utility for vaccinated consumers given by $v - \gamma - r\left[1 - \left(1 - G(t)\right)e_n\right] - L_n$. Therefore, the vaccine demand is realized as $\overline{m}[1 - \gamma + r\left(1 - G(t)\right)e_n - L_n]$.

For Case AA, we find the optimal ordering quantity $q_2^{SE,AA*} = \max\left\{0, \mu_2\left[1 - \gamma + r\left(1 - G(t)\right)e_A - L_A\right] + \sigma_2 \Phi^{-1}(s^{SE}) - q_1\right\}$, where $s^{SE} = \frac{1-2(\gamma+w_A+c-r\left(1-G(t)\right)e_A+L_A)}{1+2(h-\gamma+r\left(1-G(t)\right)e_A-L_A)}$ represents the inventory service level of the vaccine in Stage 2.

For Case AB, we find the optimal ordering quantity $q_2^{SE,AB*} = \max\left\{0, \mu_2\left[1 - \gamma + r\left(1 - G(t)\right)e_n - L_n\right] + \sigma_2 \Phi^{-1}(s^{SE}) - q_1\right\}$, where $n = \begin{cases} A, & if\ e_A > e_B \\ B, & if\ e_A \leq e_B \end{cases}$, $s^{SE} = \begin{cases} \frac{1-2(\gamma+w_B+c-r(1-G(t))e_B+L_B)}{1+2(h-\gamma+r\left(1-G(t)\right)e_B-L_B)}, & if\ e_A > e_B \\ \frac{1-2(\gamma+w_B+c-r\left(1-G(t)\right)e_B+L_B)}{1+2(h-\gamma+r\left(1-G(t)\right)e_A-L_A)}, & if\ e_A \leq e_B \end{cases}$.

Proposition 5.5. *(i) No matter in Case AA or AB, we have* $s^{SE} < s$. *(ii) For* $i = AA$ *or* AB, *when* $\mu_2 > \bar{\mu}^{SE,i}$, *we have* $q_2^{SE,i*} > 0$; *when* $\mu_2 \leq \bar{\mu}^{SE,i}$, *we have* $q_2^{SE,i*} = 0$, *where* $\bar{\mu}^{SE,i} = \frac{q_1-\sigma_2\Phi^{-1}(s^{SE})}{1-\gamma+r(1-G(t))e_n-L_n}$, *and* $n = \begin{cases} A, & if\ i = AA\ or\ (i = AB\ and\ e_A > e_B) \\ B, & if\ i = AB\ and\ e_A \leq e_B \end{cases}$.

Proposition 5.5 reveals the impacts of side effects on the government's optimal ordering policy in Stage 2. First, it is understandable that the side effect will reduce the individual's willingness to vaccinate, which decreases the government's ordering quantity in Stage 2. Moreover, we find that the government is less likely to place an order in Stage 2 if the vaccines' side effect is taken into consideration. This finding indicates that the vaccines' side effect will reduce the efficiency of information updating.

Then, using the same approach used in the basic model, we can derive the expected benefit-to-go and the corresponding optimal order quantity for the government in Stage 1 in the two cases (P.S.: The detailed expressions can be found in Appendix B). To figure out whether it is appropriate for the government to change its vaccine supplier after information updating when considering the side effects, we conduct numerical analysis (see Figure A5-17 in Appendix A) and obtain Observation 5.5. Note that, we set $\xi_{A,y} = 0.4$, $\xi_{A,e} = 0.3$, $\xi_{B,y} = 0.5$, and $\xi_{B,e} = 0.4$, which follows the assumption that the vaccine's side effect is more prevalent among the youth group than the elder group (Riad et al., 2021). Meanwhile, two different cases regarding the infection rate are examined, i.e., the case when r is small ($r = 0.4$) and the case when r is large ($r = 0.9$).

Observation 5.5. *(i) When* r *is relatively small, social welfare is higher in Case AA if* $e_A \leq e_B$ *or* α_y *is relatively small; otherwise, social welfare is higher in Case AB. (ii) When* r *is relatively large, social welfare is higher in Case AA if* $e_A > e_B$ *or* α_y *is relatively small; otherwise, social welfare is higher in Case AB.*

Observation 5.5 implies that in Stage 2, changing vaccine supplier is not always beneficial to social welfare when considering the side effects. The government should carefully make decisions based on the infection rate, the vaccines' efficacy levels, and the age group distribution in the society. Specifically, when the disease's infection rate is relatively low (resp. high), only when the youth group's proportion is large (i.e., fewer elderly people), the government is recommended to choose an alternative vaccine supplier (i.e., Case AB) with a lower (resp. higher) efficacy level after information updating. This result indicates that (i) no matter whether the infection rate is low or high, the government may still change its vaccine supplier after information updating. To be specific, Supplier B with a higher efficacy level (compared with Supplier A) is preferred when the infection rate is low. Otherwise, Supplier B with a lower efficacy level is preferred when the infection rate is high. This finding is consistent with the one derived in the basic model (i.e., Observation 5.3), which shows the robustness of our study. (ii) In places with a severe age problem, i.e., a large proportion of elders, the government is advised not to change its vaccine supplier since social welfare will suffer due to the impact of side effects.

5.5 Summary

Motivated by real-world cases of governments' vaccine procurement policies under the COVID-19 pandemic (especially during the early stage of the pandemic) as well as the emergence of digital technologies, we build a two-stage two-ordering inventory model with Bayesian information updating. We investigate and derive the government's optimal dynamic vaccine ordering policy that optimizes social welfare. We consider the scenario that the government can make its initial vaccine ordering decision from one supplier at the first stage and then is allowed to adjust its ordering decision at the second stage (i.e., whether to make an order, whether to change the supplier, and corresponding order quantity at the second stage) based on the updated demand information. Our analyses yield some implications and suggestions for the government regarding its optimal order time point, order quantities, and supplier selection decisions. We further consider the use of blockchain technology for cold chain management and also explore the impacts of vaccine's side effects. The significant implications derived from our study are summarized as follows.

Optimal order policy: First, the government need not order the vaccine as early as possible. When the infection rate is relatively low, the government should order nothing at the first stage and place all the orders at the second stage with the updated demand information. Since a low infection rate leads to weak demand, the government does not need to over-order vaccines at the very beginning. Whereas when the infection rate is high, the government should order vaccines in the first stage. Then, in the second stage, both the higher vaccine efficacy level and the larger infection rate will increase the government's willingness to order, as the vaccine demand will be remarkably increased under these circumstances. These findings indicate the necessity for information updating that allows the government to supplement its order in the second stage, under certain conditions dynamically. Note that, when variants of the virus (such as the notorious Omicron) are expected, the government is more likely to order vaccines in both stages. Besides, when considering the vaccine's side effects, we find that the government's order quantity in the second stage would be reduced.

Supplier selection: In the second stage, when the government faces two alternative vaccine suppliers, it should carefully select the best one based on the disease's infection rate, which varies from place to place (Abedi et al., 2021). Specifically, when the infection rate is low, the government should choose the supplier with a higher efficacy level (compared with the one in the first stage) upon information updating. When the infection rate is high, choosing the supplier with a lower efficacy level is more beneficial. The rationale behind is that the high (low) infection rate has already induced the government to order vaccines from the supplier with a high (low) efficacy level in the first stage. Hence providing a choice (i.e., a supplier with an opposite efficacy level) for the consumers in the second stage can help increase social welfare. Finally, when the infection rate is moderate, the government should continue to order vaccines from the same supplier as in the first stage. In order words, the government does not have to choose an alternative vaccine supplier after information updating, especially in places with a moderate infection rate. These implications remain valid if the government considers the vaccine's side effects when making decisions.

Blockchain adoption: In the basic model, we notice that an increase in shipping time inevitably reduces the vaccine order quantity and harms social welfare. We hence propose the measure of blockchain adoption to eliminate such negative impacts on the vaccine cold chain. Our findings reveal that with blockchain adoption, the government is willing to order more vaccines at the first stage, regardless of the shipping time, while may reduce its order quantity after demand information updating in the second stage when the shipping time is relatively short. This finding implies that the blockchain adoption reduces the significance of information updating. Then, regarding social welfare improvement, blockchain adoption is recommended only when the shipping time is relatively long or when the government decides not to change its vaccine supplier (in a place with a high infection rate).

Chapter 6 Concluding Remarks

6.1 Conclusions

Realizing a series of challenges brought by COVID-19 (including demand and supply disruptions, reshaped consumer behavior, demand uncertainty, etc.) to supply chain management (SCM) and social performance, this doctoral thesis aims to determine the insights (including optimal decisions and managerial findings) that improve supply chain performance and enhance social welfare under/after the pandemic. A practice-based analytical modeling approach is adopted to examine the operational challenges from three different perspectives: (i) Service operations: the value of WhatsApp shopping service operations in helping the company to survive the pandemic and enhancing social welfare. (ii) Production: the government's role and the impacts of government's subsidy on mask production and social welfare. (iii) Procurement: the government's optimal vaccine ordering strategy that maximizes the total social welfare. Some major findings are extracted and discussed as follows.

The value of WhatsApp shopping service operations: To evaluate how the new normal of service operations, i.e., "WhatsApp Shopping Service Operation" (WSO), impacts on the company's performance under the pandemic, we collect primary data from real-world cases and theoretically explore the value of WSO. We build a standard consumer utility-based model to derive the firm's optimal pricing and employment decisions under different cases. We evaluate the impacts of COVID-19 and values of WSO implementation from the "Worker-Consumer-Company" (WCC) welfare perspective. Our results interestingly imply that WSO is superior to the traditional online channel in terms of keeping business under the pandemic; meanwhile, implementing WSO can help stimulate demand in the physical store. However, whether WSO is effective to help increase the firm's profit and WCC welfare depends on both consumer type's distribution and consumers' fear of infection. We define the profit-welfare-improvement (PWI) outcome for the case in which both the firm's profit and Worker-Consumer-Company (WCC) welfare can be improved simultaneously. Our results show that the PWI outcome can be only achieved when the consumers' fear of infection is moderate and there are more WSO type consumers in the market. Particularly, when the consumers' fear of infection is moderate while there are fewer WSO type consumers in the market, we suggest the government to adopt an incentive mechanism (e.g., providing a subsidy) to support the firm's WSO implementation, which can be an effective way to help the firm survive COVID-19 as well as improve WCC welfare. However, when the consumers' fear of infection is polarized (i.e., extremely low or high), WSO is never recommendable. We further propose that the government's subsidy for WSO implementation could be an effective way to help the firm improve its profit and WCC welfare. We also check the robustness of our study by extending the model to consider endogenous consumer type, endogenous service level, and WCC-welfare-oriented firm. Note that, although the pandemic was over, the consumer's change of behavior is long-lasting. Therefore, the proposed implications remain valid for the firms aiming to adapt to the new normal in the post-pandemic stage.

The government's role in mask production: Motivated by an interview with a mask manufacturer as well as the observed real-world practices, we utilize an infection transmission model to capture the social health risk during the COVID-19 outbreak and analytically examine government subsidies and policies in a mask supply chain (MSC). The government aims at maximizing social welfare which includes the manufacturer's profit, consumer surplus, social health risk, and government's subsidy expenditure. Results indicate that when the mask price is not controlled (i.e., the manufacturer decides it), the manufacturer and consumer subsidy programs are equally efficient in enhancing consumer surplus as well as reducing harms on social health risk under COVID-19. Thus, the government can conduct a subsidy scheme that is easier to implement in practice. For instance, for those places where the digital payment is popular (e.g., Mainland China), consumer subsidy is more recommended as it is easier for the government to track the consumer's purchase and grant the needed subsidy. However, we surprisingly find that the government's excessive intervention will cause the disequilibrium in the MSC. When the price or the manufacturer's dishonest behavior is fully controlled by the government, subsidizing the MSC is not always advisable. Besides, our findings are consistent with the public interest theory; that is, the proper implementation of dishonesty prevention and pricing control policies can improve social welfare but sacrifice consumer surplus. Importantly, we find that in the post-pandemic stage when both original infection rate and supply disruption are relatively low, the subsidy program is no longer effective for social welfare. This may why in real world cases, Chinese government cancelled the subsidy program in August 2020 when the pandemic was basically in control at that time. Our results contribute to healthcare operations management and generate managerial insights for mask production under/after COVID-19 with industrial validation.

The government's optimal vaccine ordering strategy: During the COVID-19 pandemic, governments faced various vaccine choices having different efficacy and availability levels at different time points. To provide guidance on government's optimal vaccine ordering strategy, a two-stage vaccine ordering problem is investigated for a government who orders from a first and only supplier in the first stage, and either the same supplier or a new second supplier in the second stage. Between the two stages, potential demand information for the vaccine is collected to update the forecast. The results indicate that the government should select its vaccine supplier based on the disease's infection rate in the society. When the infection rate is low, the government should change the supplier with a higher efficacy level in the second stage (compared with the one in the first stage) after information updating. When the infection rate is high, changing to the supplier with a lower efficacy level in the second stage is more advisable. When the infection rate is moderate, the government should order vaccines from the same supplier in both stages. Besides, the extended analyses uncover that the use of blockchain is recommended when (i) the shipping time is relatively long, or (ii) the government decides not to change its vaccine supplier after information updating (in a place with a high infection rate). Moreover, when considering the vaccine's side effects, for places with many older adults, the government should not change its vaccine supplier after information updating.

To summarize, this doctoral thesis contributes to the development of SCM under/after the unexpected pandemics (e.g., COVID-19) from both the academia and practical perspectives. In academia, this study use analytically methods to explore the optimal decisions of service operations, production, and procurement for the company and the government. In practices, our interview results validate the major findings and provide insights for future research direction. All the findings help the supply chains to better survive the pandemic as well as achieve sustainable development.

6.2 Future Studies

No research is perfect. In this subchapter, several possible directions for future research are proposed and discussed.

First, extending current model settings can help derive more interesting findings. For instance:

(i) *Multi-period problems:* The two-period or M-period (M > 2) problems can be considered. (a) In mask production, it will be meaningful to explore the manufacturer competition in a two-period scenario (Chambers et al. 2006), in which the influence of competing mask manufacturers'

leadership on subsidy decisions can be examined. (b) In vaccine ordering, generalizing the problem to the M-period setting has a good practical value while it will be analytically challenging to do so. Hence, for future research, other optimization models and methods could be considered for this extension (Kaminsky and Wang, 2019).

(ii) *Continuous time models:* Considering a dynamic model with the influence of time (e.g., a continuous time model) should be interesting, in which we can explore the case when time plays a role. For example, when investigating the value of blockchain in vaccine ordering, the efficiency of blockchain can be dependent on time.

(iii) *Uncertainty:* Modeling market uncertainty is important under COVID-19. An alternative Bayesian model can be adopted in vaccine ordering problems, where both the mean and variance of the customer population are unknown and can be updated in the second stage (Choi et al., 2006). For service operations, it will be interesting to evaluate the impacts of firm's risk attitude for market uncertainty on its WSO strategy.

(iv) *Supply chain structure:* New insights can be derived under different supply chain structures, e.g., horizontal and vertical collaborations (Xu et al. 2023c). For example, the study of dynamic vaccine ordering policy can be extended into a horizontal collaboration case, when two competing vaccine manufacturers cooperate with each other to develop a new vaccine. The new model setting will significantly affect the government's ordering decisions.

Second, there are some limitations of the interviews in this thesis, which can be further extended:

(i) *Structured interview:* We conduct semi-structured interviews in this study, which usually face the problem of low validity. Hence, for the future research, structured interviews are welcomed to improve the validity of the research findings.

(ii) *Cross-country interview:* Due to the unavailability of data, we only include the data from an interview in China, which may be incomprehensive for global SCM. In the future, it will be interesting to explore the differences of operations among different countries by a cross-country or cross-cultural study.

Finally, various influential factors and research questions can be further examined based on the current studies. For example:

(i) *Transportation issues:* Apart from the three major issues discussed in this thesis (i.e., service operations, production, and procurement), "transportation" is another essential topic in SCM that

can be explored in the future. Since is more related to the operational research domain, we do not include it in this OM study.

(ii) *Return policy:* It should be interesting to consider the return policy for WSO. Since consumers cannot assess the fitness of the product by purchasing through WSO, product return is likely to happen; however, return policy may have the potentially damaging impact on the retailer (Xu et al., 2018b).

(iii) *Budget constraint:* Since the government's decision plays a critical role in this study, the government's budget constraint can be further considered (Eryarsoy et al. 2023). Owing to the limited budget, both the subsidy allocation strategy and the vaccine ordering policy may be different.

(iv) *Supply disruption:* It will be significant to further explore the impacts of supply disruption on both the firm and government's decisions, especially in the mask production and vaccine ordering problems, as it is a critical issue faced by most manufacturers during the pandemic (Ivanov, 2020).

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Appendix A —— Supplementary Materials

Table A1-1. Notation table for Figure 2-1.

Classification	Notations	Meanings
Research issues	DD	Demand disruption
	UD	Uncertain demand
	CB	Consumer behavior
	SD	Supply disruption
	RA	Resource allocation
	TI	Transportation issues
Pandemic stages	PRE	Pre-pandemic
	DUR	During-pandemic
	POST	Post-pandemic
3Rs	R1	Responsiveness
	R2	Resilience
	R3	Restoration

Table A2-1. Government subsidies for MSCs during the COVID-19 outbreak[18].

Places	Subsidizing manufacturers	Subsidizing consumers	Checking for dishonesty[19]	Price control
Hong Kong	✓		✓	
Singapore		✓		
Mainland China	✓	✓		✓
Japan	✓		**?**	
Germany	✓		**?**	
Italy	✓		**?**	✓

[18] We focus on the countries which have claimed their subsidy programs in public, we hence can find the relevant news from public resources.

[19] We have searched but cannot find information regarding whether governments from Japan, Germany and Italy have imposed any checking mechanisms (P.S.: We hence put "**?**" as the notation in the table). This point is tricky. Conventional wisdom indicates that governments usually would have some mechanisms to avoid dishonesty for their subsidies. However, COVID-19 is special as even governments staff members may need to work at home and "city-lockdown" rules may be imposed. As such, we speculate that some of these governments actually do not impose any formal checking mechanisms. This also partially motivates us to explore (i) whether it is wise to check and (ii) suppose that it is wise to check, whether the use of blockchain technology can help.

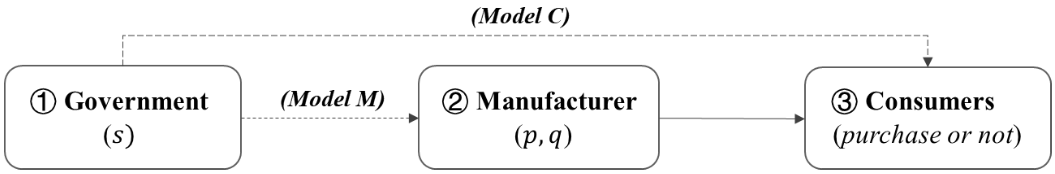


Figure A3-1. The basic model in Chapter 4.
(P.S.: The numbers 1, 2 and 3 represent the decision sequence; decisions are placed inside the brackets, e.g., whether to implement Model C or Model M and the respective *s* are decided by the government.)

Table A4-2. The list of notations in Chapter 4.

Notation	Meaning
v	Consumer valuation.
s	Government's subsidy.
q	Product quality.
p	Unit selling price.
ε	Manufacturer's production yield (of qualified product).
d_0	Actual market demand of mask.
$\tilde{D}$	Market demand which can be satisfied by the manufacturer, where $\tilde{D}=\tilde{\theta}d_0$.
$\tilde{Q}$	Manufacturer's real production output, where $\tilde{Q}=\tilde{\theta}d_0/\varepsilon$.
k	Fixed part of unit production cost.
ξ	Coefficient of quality on unit production cost.
λ	Coefficient of quality improvement cost.
τ	Infection rate of the COVID-19 disease.
δ_b and δ_{nb}	Infection probabilities respectively for the consumers buying and not buying the mask, where $\delta_b=\tau(1-q)$ and $\delta_{nb}=\tau$.
$\tilde{\theta}$	Supply disruption, where $\tilde{\theta}$ is a random variable with a probability density function $g(\tilde{\theta})$ and mean $\theta\in[0,1]$. The lower $\tilde{\theta}$ means the stronger supply distribution.
α, β, γ, and η	The weight of manufacturer's profit, consumer surplus, health risk, and government expenditure in social welfare, where $\alpha+\beta+\gamma+\eta=1$.
p_0	Price controlled by the government.
ϕ	Discount factor for the amateur manufacturer (i.e., Manufacturer 2).
F_i	Government's fixed subsidy implementation cost, where *i=C or M.*
F_G	Government's fixed price-control cost.
F_{BNA}	Manufacturer's fixed blockchain implementation cost.
c_{BNA}	Manufacturer's unit blockchain implementation cost.
Π	Manufacturer's profit.

CS	Consumer surplus.
R	Health risk.
SW	Social welfare.

Remarks: The subscripts "C", "M", "CG" and "MG" denote "Model C", "Model M", "Model CG" and "Model MG", respectively; the superscripts "A", "NA", "BNA", and "CM" represent "Dishonesty Anticipated", "Dishonesty Not Anticipated", "Using Blockchain", and "Competing Manufacturers" cases, respectively.

Table A5-3. Impacts of the infection rate on MSC performance with supply disruption (we set $\alpha=\beta=\gamma=\eta=0.25$, $k=0.3$, $\varepsilon=0.8$, $\xi=0.2$, $\lambda=0.3$, and $F_{M/C}=0.1$)[20].

(a) When supply disruption is weak ($\theta=0.9$).

τ	$\Delta\prod$	ΔCS	ΔR	ΔSW
0.27	0.3670	0.1836	-0.0059	0.0117
0.29	0.5268	0.2641	-0.0184	0.0112
0.31	0.7949	0.3996	-0.0446	0.0078

(b) When supply disruption is moderate ($\theta=0.5$).

τ	$\Delta\prod$	ΔCS	ΔR	ΔSW
0.25	0.1465	0.0732	0.0000	0.0061
0.275	0.1840	0.0920	-0.0021	0.0064
0.3	0.2346	0.1175	-0.0059	0.0066
0.325	0.3053	0.1534	-0.0125	0.0065
0.35	0.4092	0.2063	-0.0241	0.0058

(c) When supply disruption is strong ($\theta=0.1$).

τ	$\Delta\prod$	ΔCS	ΔR	ΔSW
0.25	0.0293	0.0146	0.0000	0.0012
0.275	0.0306	0.0153	-0.0001	0.0012
0.3	0.0321	0.0161	-0.0002	0.0013
0.325	0.0336	0.0168	-0.0003	0.0013
0.35	0.0353	0.0177	-0.0004	0.0013
0.375	0.0371	0.0186	-0.0006	0.0013
0.4	0.0391	0.0196	-0.0008	0.0014
0.425	0.0412	0.0207	-0.0010	0.0014
0.45	0.0435	0.0219	-0.0013	0.0015
0.475	0.0460	0.0232	-0.0017	0.0015
0.5	0.0487	0.0246	-0.0020	0.0016

[20] All the data set in the numerical studies satisfy the respective physical meanings and follow the model assumptions. For example, we set $\alpha=\beta=\gamma=\eta=0.25$, $k=0.3$, $\varepsilon=0.8$, $\xi=0.2$, $\lambda=0.3$, and $F_{M/C}=0.1$ and derive the results in Table A4-3. Here, the parameters α, β, γ and η represent the weights of four different parts on social welfare, which should satisfy the condition $\alpha+\beta+\gamma+\eta=1$; the parameters k, ε, ξ, λ, and $F_{M/C}$ denote the costs, which are scaled down between 0-1 according to an uniform standard.

We use the software MATLAB as a tool to depict the numerical results for Chapter 5 below. In our numerical analyses, all the data we set follow the model assumptions and can help show the effects clearly. The general settings are as follows: we let $d_0 = 1000$, $\delta = 500$, $\sigma_1 = 100$, $\omega = 0.8$, $\mu_0 = 1000$, $\gamma = 0.1$, $r = 0.5$, $t = 0.2$, $h = 0.2$, $c = 0.02$, $B = 0.1$, $F = 10$, $\xi_{A,y} = 0.4$, $\xi_{A,e} = 0.3$, $\xi_{B,y} = 0.5$, $\xi_{B,e} = 0.4$, $e_A = 0.9$, $e_B = 0.6$, $w_A = 0.2$, and $w_B = 0.1$ for the case when $e_A > e_B$, and $e_A = 0.9$, $e_B = 0.95$, $w_A = 0.2$, and $w_B = 0.3$ for the case when $e_A \leq e_B$; more specific settings can be checked in each figure.

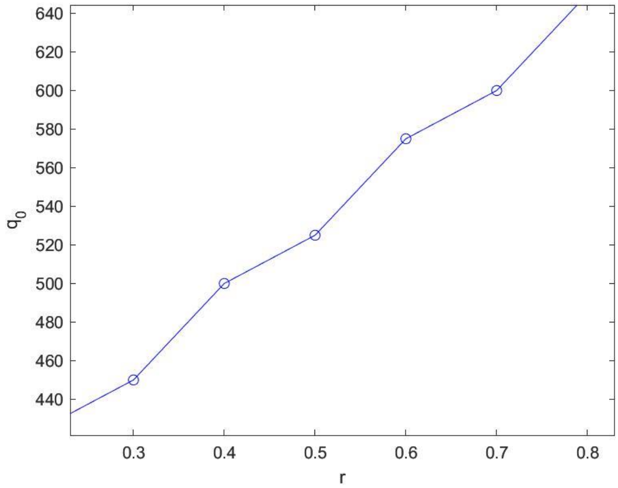


Figure A1-1. Optimal order quantity at Stage 1 in Case AA vs. the infection rate.

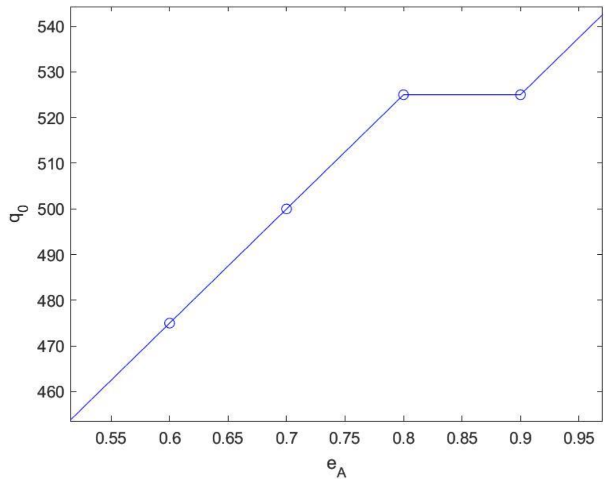


Figure A2-2. Optimal order quantity at Stage 1 in Case AA vs. the efficacy level of Supplier A's vaccine.

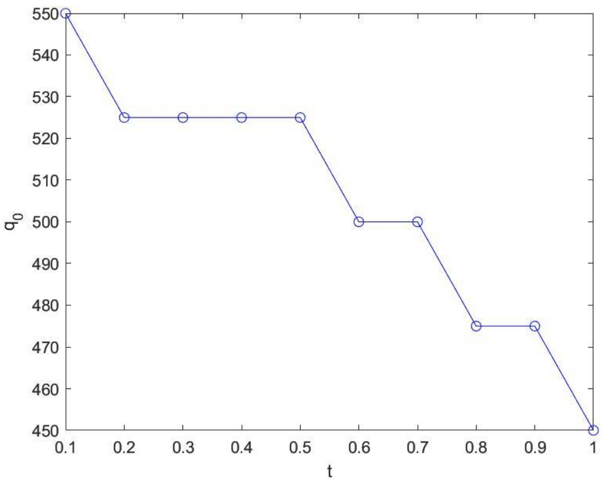


Figure A3-3. Optimal order quantity at Stage 1 in Case AA vs. the shipping time.

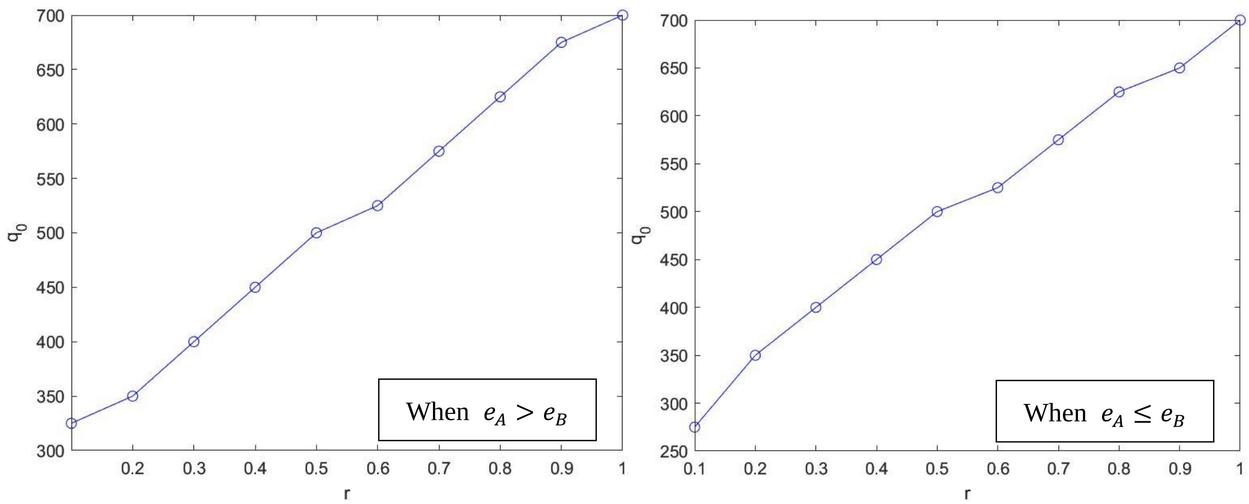


Figure A4-4. Optimal order quantity at Stage 1 in Case AB vs. the infection rate.

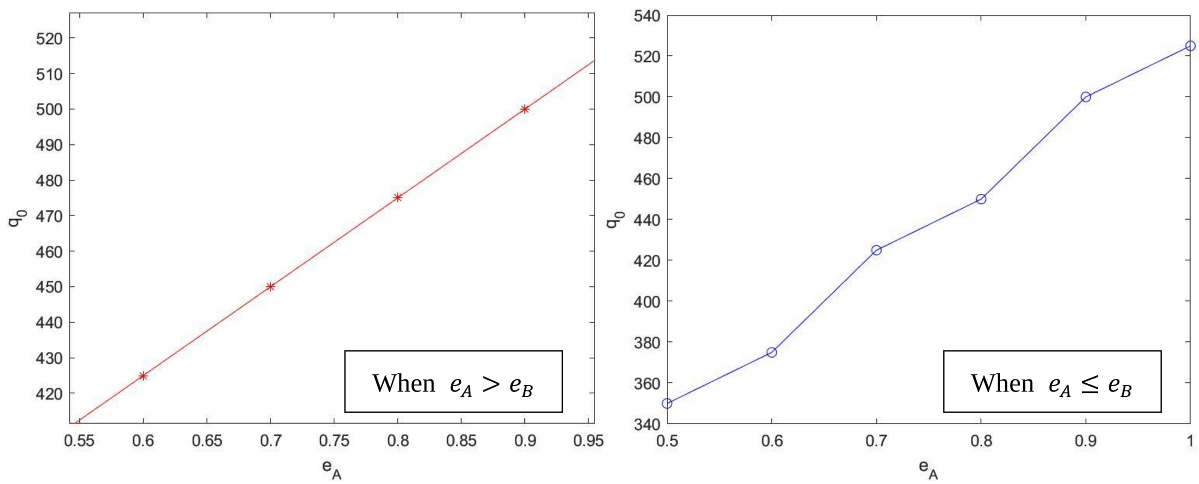


Figure A5-5. Optimal order quantity at Stage 1 in Case AB vs. the efficacy level of Supplier A's vaccine.

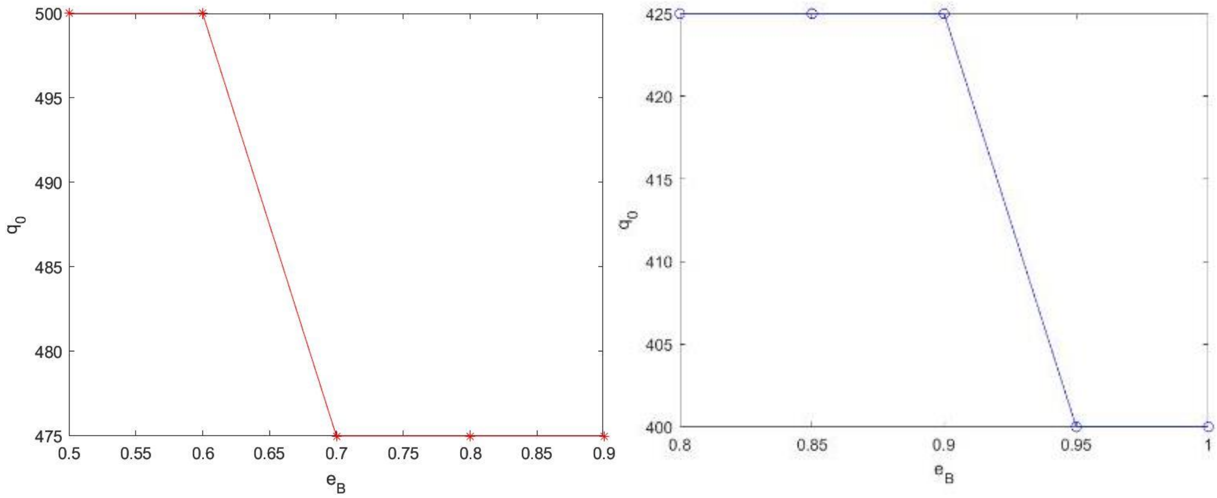


Figure A6-6. Optimal order quantity at Stage 1 in Case AB vs. the efficacy level of Supplier B's vaccine.

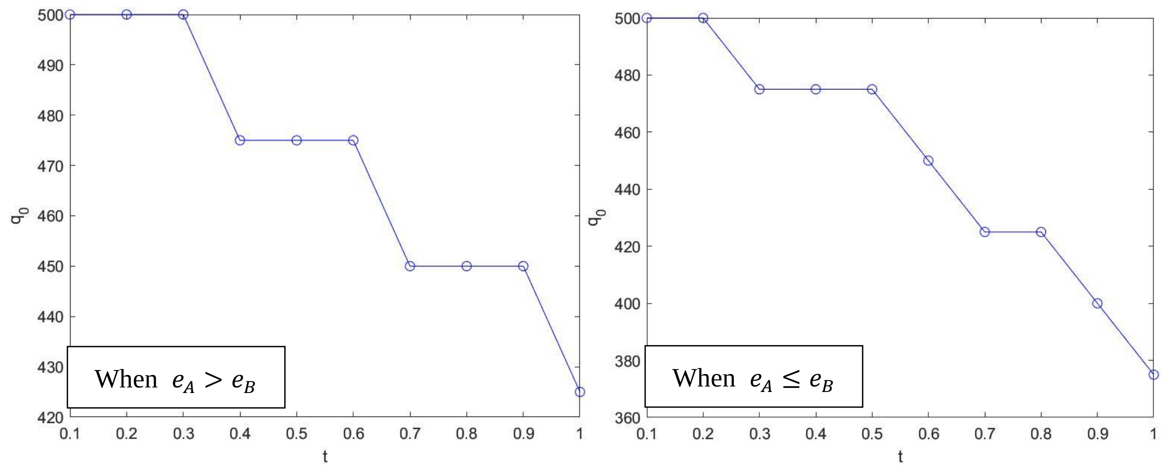


Figure A7-7. Optimal order quantity at Stage 1 in Case AB vs. the shipping time.

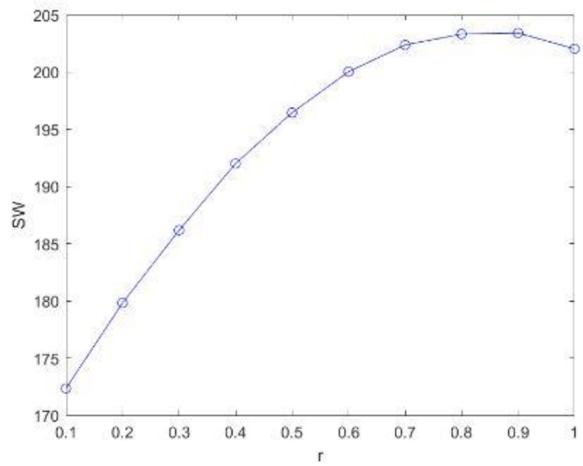


Figure A8-8. Social welfare in Case AA vs. the infection rate.

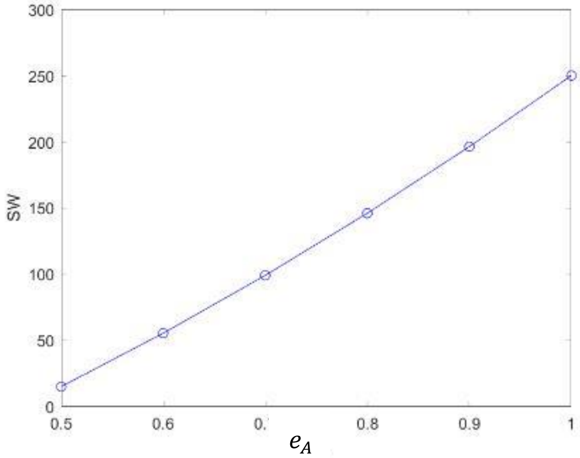


Figure A9-9. Social welfare in Case AA vs. the efficacy level of Supplier A's vaccine.

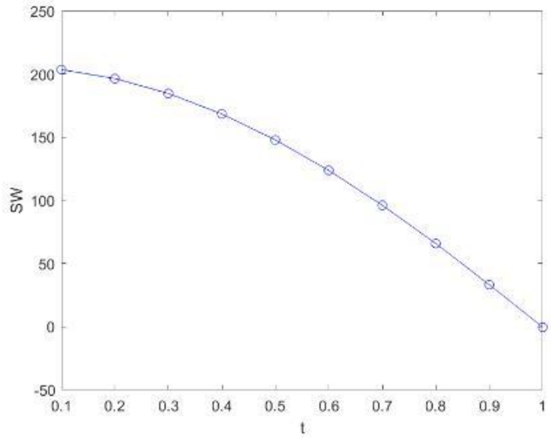


Figure A10-10. Social welfare in Case AA vs. to the shipping time.

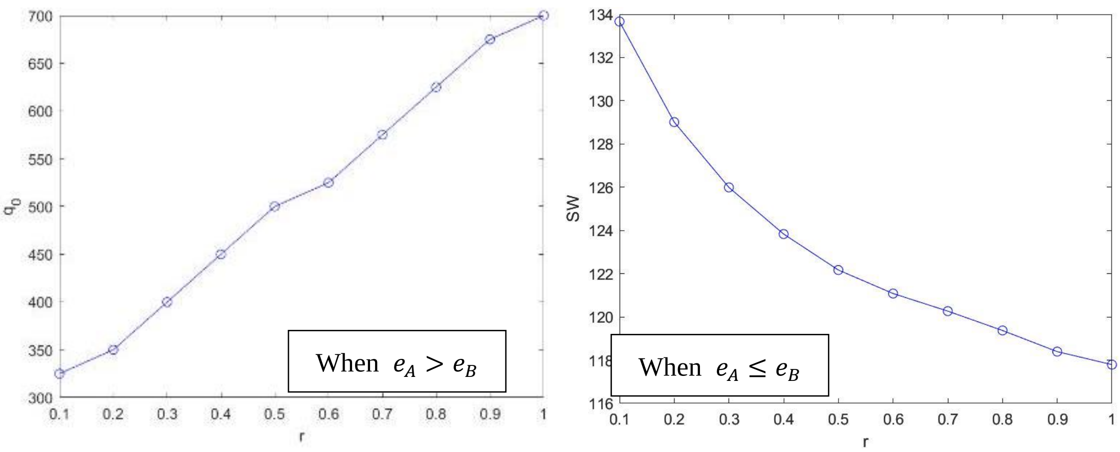


Figure A11-11. Social welfare in Case AB vs. the infection rate.

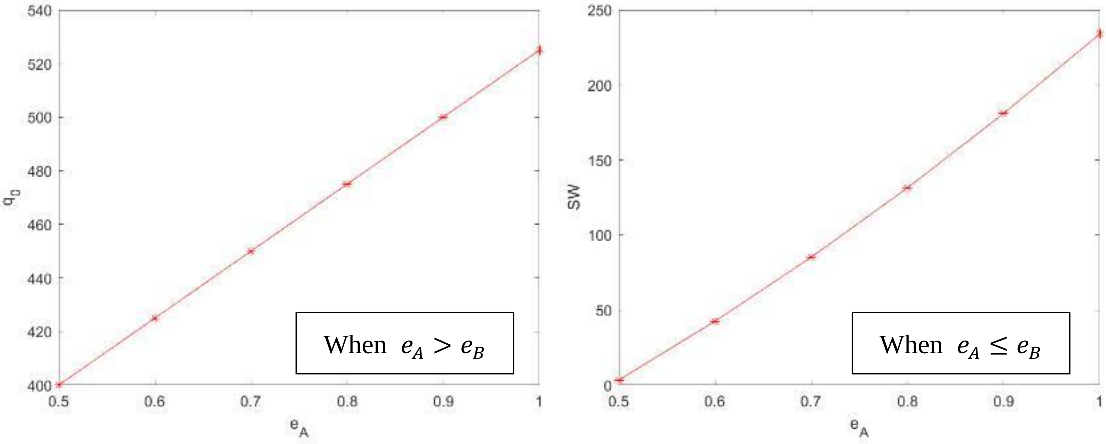


Figure A12-12. Social welfare in Case AB vs. the efficacy level of Supplier A's vaccine.

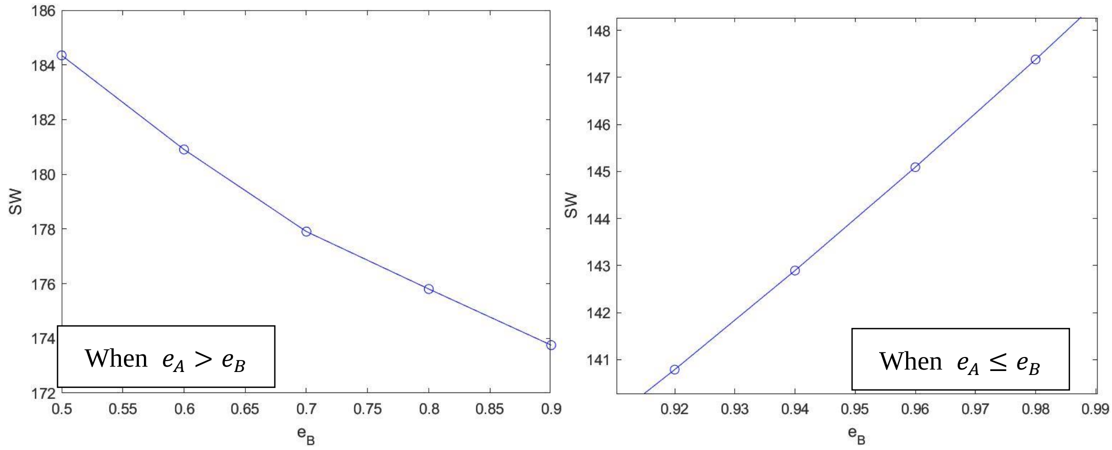


Figure A13-13. Social welfare in Case AB vs. the efficacy level of Supplier B's vaccine.

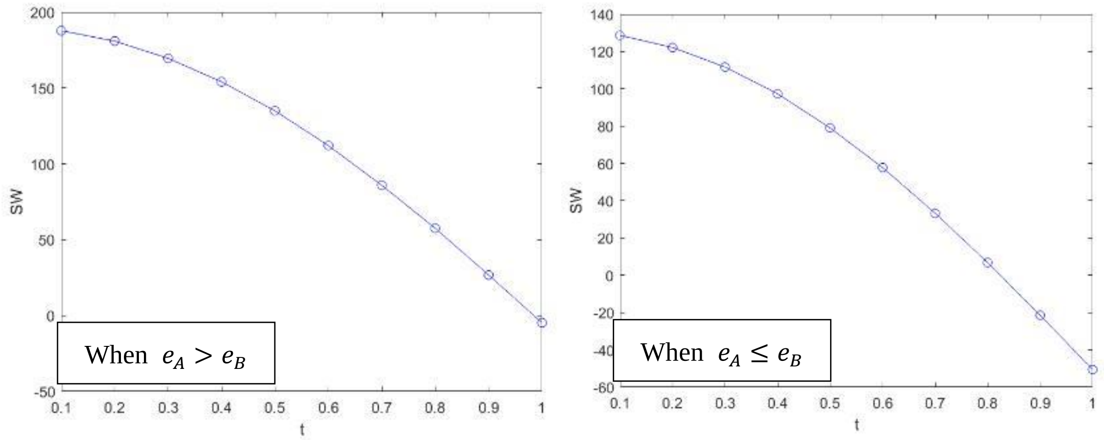


Figure A14-14. Social welfare in Case AB vs. the shipping time.

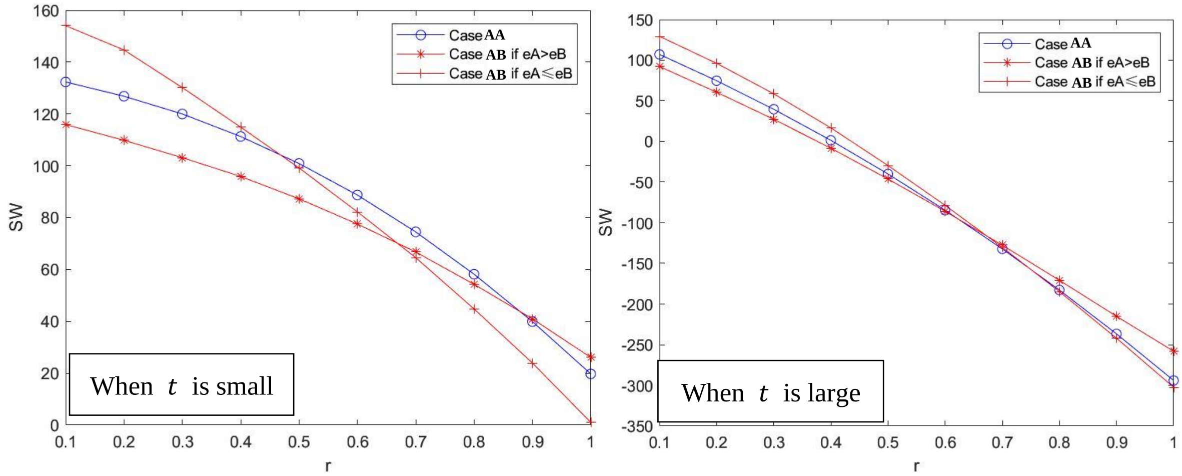


Figure A15-15. Comparisons of social welfare in Cases AA and AB vs. the infection rate (We let $t = 0.5$ when t is small and $t = 1$ when t is large).

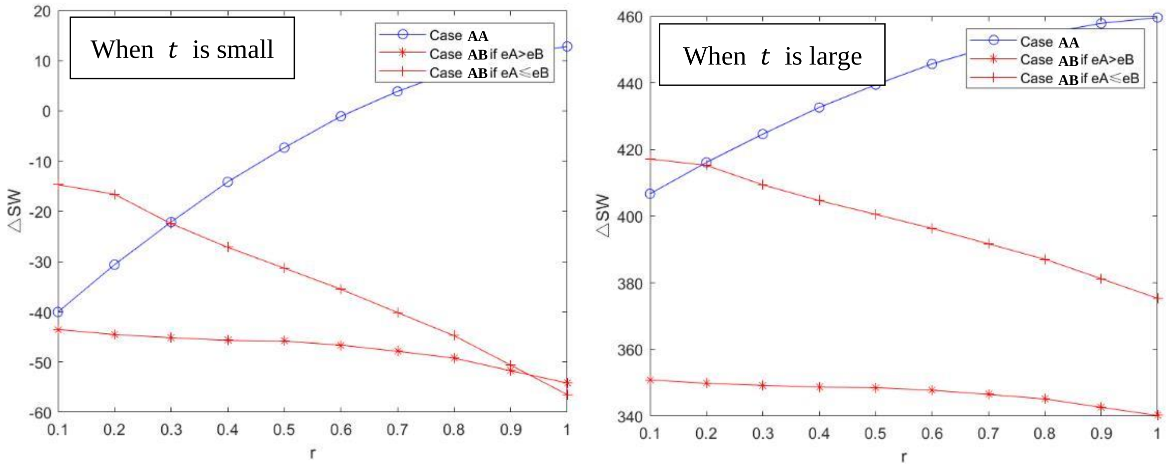


Figure A16-16. The value of blockchain adoption in Cases AA and AB vs. the infection rate (We let $t = 0.2$ when t is small and $t = 1$ when t is large).

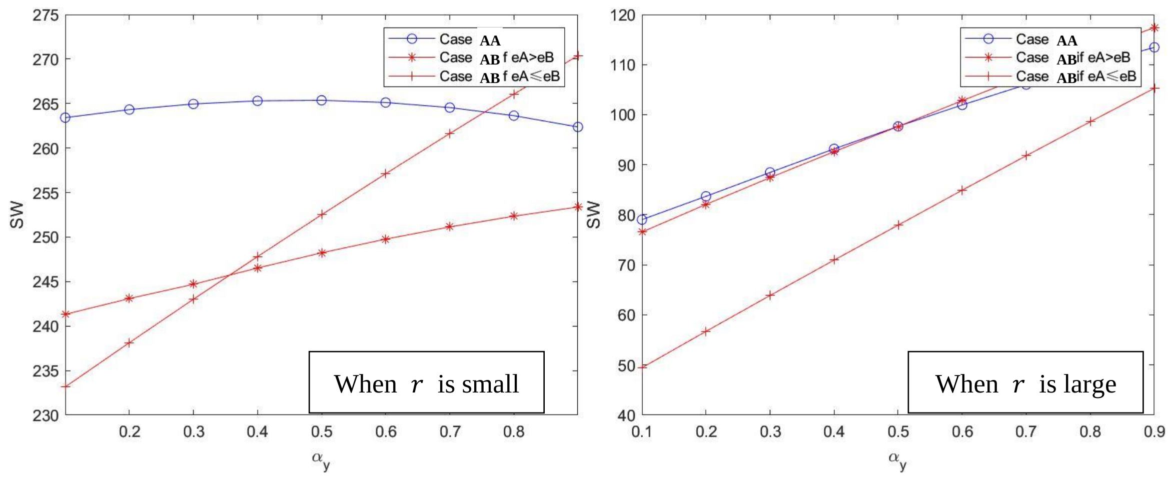


Figure A17-17. Comparisons of social welfare in Cases AA and AB vs. the proportion of youth age group when considering the existence of side-effect (We let $r = 0.4$ when r is small and $r = 0.9$ when r is large).

Table A5-1. Range of critical infection rate for different vaccines (We let $d_0 = 1000$, $\delta = 500$, $\sigma_1 = 100$, $\omega = 0.8$, $\mu_0 = 1000$, $\gamma = 0.1$, $t = 0.2$, $h = 0.2$, $w_A = 0.1$, and e_A various from 0.5 to 1).

Efficacy level	**Examples of vaccine supplier**	**Critical infection rate**
50% ~ 85%	Sinovac, Johnson & Johnson, Astrazeneca	<0.35
85% ~ 90%	Novavax	0.35 ~ 0.85
90% ~ 100%	Pfizer-BioNTech, Moderna	>0.85

Appendix B —— All Proofs

Proof of Lemma 3.1: Without COVID-19, the optimal price ($p_{PPS}^{\overline{COV}*}$) and employment level ($y_{PPS}^{\overline{COV}*}$) can be obtained from solving the first order conditions $\frac{\partial \pi_{PPS}^{\overline{COV}}}{\partial p_{PPS}^{\overline{COV}}} = 1 + c - 2p + ksy + \beta = 0$ and $\frac{\partial \pi_{PPS}^{\overline{COV}}}{\partial y_{PPS}^{\overline{COV}}} = ks(-c + p - \beta) - 2s^2 y\lambda - f = 0$, and then substituting with each other. To ensure concavity, we derive the determinant of Hessian Matrix $H_{PPS}^{\overline{COV}} = \begin{vmatrix} -2s^2\lambda & ks \\ ks & -2 \end{vmatrix} = s^2(4\lambda - k^2)$, and $H_{PPS}^{\overline{COV}} > 0$ when $\lambda > \frac{k^2}{4}$.

Then, we substitute $p_{PPS}^{\overline{COV}*}$ and $y_{PPS}^{\overline{COV}*}$ into $D_{PPS}^{\overline{COV}} = 1 - p + ksy$, and it is easy to obtain $D_{PPS}^{\overline{COV}*}\left(p_{PPS}^{\overline{COV}*}, y_{PPS}^{\overline{COV}*}\right) = \frac{fk + 2s(-1 + c + \beta)\lambda}{s(k^2 - 4\lambda)}$ and $\frac{\partial D_{PPS}^{\overline{COV}*}}{\partial \beta} \leq 0$. So, the $D_{PPS}^{\overline{COV}*} \geq 0$ when $\beta < \beta_{PPS}^{\overline{COV}} = 1 - c - \frac{fk}{2s\lambda}$ can be yield. (Q.E.D.)

Proof of Lemma 3.2: With COVID-19 and without the introduction of WSO channel, the optimal price (p_{PPS}^{COV*}) and employment level (y_{PPS}^{COV*}) can be derived from solving the first order conditions $\frac{\partial \pi_{PPS}^{COV}}{\partial p_{PPS}^{COV}} = 1 + c - 2p + ksy + \beta - \xi = 0$ and $\frac{\partial \pi_{PPS}^{COV}}{\partial y_{PPS}^{COV}} = ks(-c + p - \beta) - 2s^2 y\lambda - f = 0$, and then substituting with each other. To ensure concavity, we derive the determinant of Hessian Matrix $H_{PPS}^{COV} = \begin{vmatrix} -2s^2\lambda & ks \\ ks & -2 \end{vmatrix} = s^2(4\lambda - k^2)$ and $H_{PPS}^{\mathrm{COV}} > 0$ when $\lambda > \frac{k^2}{4}$.

Then we substitute p_{PPS}^{COV*} and y_{PPS}^{COV*} into $D_{PPS}^{COV} = 1 - p + ksy - \xi$, and it is easy to obtain $D_{PPS}^{COV*}(p_{PPS}^{COV*}, y_{PPS}^{COV*}) = \frac{fk + 2s\lambda(-1 + c + \beta + \xi)}{s(k^2 - 4\lambda)}$ and $\frac{\partial D_{PPS}^{COV*}}{\partial \beta} \leq 0$. So that, the $D_{PPS}^{COV*} \geq 0$ when $\beta \leq \beta_{PPS}^{COV} = 1 - c - \frac{fk}{2s\lambda} - \xi$ can be yield. Comparing β_{PPS}^{COV} and $\beta_{PPS}^{\overline{COV}}$, it is straightforward to see $\beta_{PPS}^{COV} \leq \beta_{PPS}^{\overline{COV}}$. (Q.E.D.)

Proof of Lemma 3.3: With the COVID-19 and conducting WSO channel, the optimal price (p_{WSO}^*) and employment level (y_{WSO}^*) can be derived from solving the first order conditions $\frac{\partial \pi_{WSO}}{\partial p_{WSO}} = 1 - \emptyset + c - 2p + ksy + \beta + g\theta = 0$ and $\frac{\partial \pi_{WSO}}{\partial y_{WSO}} = ks(-c + p - \beta) - gks\theta - 2s^2 y\lambda - f = 0$, and then substituting with each other. Where $\emptyset = (1-\theta)\xi + \theta t \geq 0$. To ensure concavity, we derive the determinant of Hessian Matrix $H_{WSO} = \begin{vmatrix} -2s^2\lambda & ks \\ ks & -2 \end{vmatrix} = s^2(4\lambda - k^2)$ and $H_{WSO} > 0$ when $\lambda > \frac{k^2}{4}$.

Then we substitute p_{PPS}^{COV*} and y_{PPS}^{COV*} into $D_{WSO} = 1 - p + ksy - \emptyset$, it is easy to obtain $D_{WSO}^*(p_{WSO}^*, y_{WSO}^*) = \frac{kf + 2s(-1+B+c+\beta+g\theta)\lambda}{s(k^2-4\lambda)}$ and $\frac{\partial D_{WSO}^*}{\partial \beta} \leq 0$. So that, the $\partial D_{WSO}^* \geq 0$ when $\beta \leq \beta_{WSO} = 1 - c - B - g\theta - \frac{kf}{2s\lambda}$ can be obtained. At last, comparing β_{WSO} with β_{PPS}^{COV}, we obtained $\beta_{WSO} \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} \beta_{PPS}^{COV}$ if and only if $\xi \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} t + g$. (Q.E.D.)

Proof of Proposition 3.1: Based on Lemma 3.3, we can obtain the first order derivatives of optimal decisions p_{WSO}^* and y_{WSO}^* w. r. t. θ. That is $\frac{\partial p_{WSO}^*}{\partial \theta} = \frac{2g\lambda - 2t\lambda + 2\lambda\xi - gk^2}{4\lambda - k^2}$ and $\frac{\partial y_{WSO}^*}{\partial \theta} = \frac{-k(g+t-\xi)}{s(4\lambda - k^2)}$. Then, it is straightforward to see that $\frac{\partial p_{WSO}^*}{\partial \theta}$ and $\frac{\partial y_{WSO}^*}{\partial \theta}$ are increasing in ξ, and we can obtain $\frac{\partial p_{WSO}^*}{\partial \theta} > 0$ and $\frac{\partial y_{WSO}^*}{\partial \theta} > 0$ when $\xi > t + g(-1 + \frac{k^2}{2\lambda})$ and $\xi > g + t$, respectively.

Secondly, by substituting optimal decisions into $\pi_{WSO}(p, y)$, the $\pi_{WSO}^*(p_{WSO}^*, y_{WSO}^*) = \frac{f^2 + fks[-1+c+\beta+\theta(g+t-\xi)+\xi] + s^2[g^2\theta^2\lambda + \lambda(-1+c+\beta+t\theta+\xi-\theta\xi)^2 + g\theta(k^2(-1+\theta)(t-\xi) + 2\lambda(-1+c+2t+\beta-t\theta+(-1+\theta)\xi))]}{s^2(4\lambda - k^2)}$ can be obtained, and we get $\frac{\partial^2 \pi_{WSO}^*}{\partial \theta^2} = \frac{2(g^2\lambda + g(k^2 - 2\lambda)(t-\xi) + \lambda(t-\xi)^2)}{4\lambda - k^2} > 0$.

By substituting optimal decisions into $WCC_{WSO}(p, y) = \pi_{WSO} + CS_{WSO} + SI_{WSO}$, the $WCC_{WSO}^*(p_{WSO}^*, y_{WSO}^*)$ can be derived. Then solving the second order derivative of WCC_{WSO}^* w. r. t. θ we have $\frac{\partial^2 WCC_{WSO}^*}{\partial \theta^2} = -\frac{X(t-\xi)}{(4\lambda - k^2)^2}$. We define $X(t-\xi) = 2g^2(k^2 - 6\lambda)\lambda + 2g(k^4 - 6k^2\lambda + 4\lambda^2)(t-\xi) + (k^4 - 6k^2\lambda + 4\lambda^2)(t-\xi)^2$ which is a quadratic function of ξ. The characteristic of $\frac{\partial^2 WCC_{WSO}^*}{\partial \theta^2}$ can be obtained by solving $X(t-\xi)$.

(a) If $\lambda \leq \frac{(3+\sqrt{5})k^2}{4}$, the negative $X(t-\xi)$ always holds, then $\frac{\partial^2 WCC_{WSO}^*}{\partial \theta^2} > 0$;

(b) If $\lambda > \frac{(3+\sqrt{5})k^2}{4}$, the negative $X(t-\xi) \Rightarrow \frac{\partial^2 y_{WSO}^*}{\partial\theta^2} > 0$ holds for $\xi \in (t - X_1, t - X_2)$ where X_1 and X_2 are two unique roots of equation $X(t-\xi) = 0$; otherwise, $X(t-\xi)$ is positive and $\frac{\partial^2 WCC_{WSO}^*}{\partial\theta^2} < 0$. (Q.E.D.)

Proof of Proposition 3.2: We define $\Delta p_{PPS} = p_{PPS}^{COV*} - p_{PPS}^{\overline{COV}*}$, $\Delta y_{PPS} = y_{PPS}^{COV*} - y_{PPS}^{\overline{COV}*}$, $\Delta\pi_{PPS} = \pi_{PPS}^{COV*} - \pi_{PPS}^{\overline{COV}*}$ and $\Delta WCC_{PPS} = WCC_{PPS}^{COV*} - WCC_{PPS}^{\overline{COV}*}$; we check characteristics of such differences one by one in the following. After solving we can obtain that $\Delta p_{PPS} = -\frac{2\lambda\xi}{4\lambda-k^2} < 0$, $\Delta y_{PPS} = -\frac{k\xi}{4\lambda-k^2} < 0$, $\Delta\pi_{PPS} = \frac{\xi[fk+s\lambda(2(-1+c+\beta)+\xi)]}{s(4\lambda-k^2)} < 0$ and $\Delta WCC_{PPS} = -\frac{\lambda\xi\left[s\left(k^2(-2+2c+\xi)-2\lambda(-6+6c+2\beta+3\xi)\right)-2fk\right]}{s(4\lambda-k^2)^2} < 0$. (Q.E.D.)

Proof of Proposition 3.3: By substituting optimal decisions under Model PPS and Model WSO into $D_{PPS}(p,y)$, physical store's demand under two models' optimal decisions can be obtained as $D_{PPS}^*(p_{WSO,}^* y_{WSO}^*)$ and $D_{PPS}^*(p_{PPS}^{COV*} y_{PPS}^{COV*})$. We define $\Delta D_{PPS}^* = D_{PPS}^*(p_{WSO,}^* y_{WSO}^*) - D_{PPS}^*(p_{PPS}^{COV*} y_{PPS}^{COV*})$, and deriving that $\Delta D_{PPS}^* = \frac{\theta(fk+s(k^2(-1+\theta)(t-\xi)+2\lambda(-1+c+t+\beta+g(-1+\theta)-t\theta+\theta\xi)))}{s(4\lambda-k^2)}$. Given that $G(\xi) = \theta(fk + s(k^2(-1+\theta)(t-\xi) + 2\lambda(-1+c+t+\beta+g(-1+\theta)-t\theta+\theta\xi)))$, we can find $\frac{\partial G(\xi)}{\partial\xi} = s(k^2(1-\theta)+2\theta\lambda) > 0$ and $\xi = \xi_{PPS} = \frac{k(f+kst(-1+\theta))+2s(-1+c+t+\beta+g(-1+\theta)-t\theta)\lambda}{k^2 s(-1+\theta)-2s\theta\lambda}$ when $\frac{\partial G(\xi)}{\partial\xi} = 0$. Therefore, $D_{PPS}^*(p_{WSO,}^* y_{WSO}^*) > D_{PPS}^*(p_{PPS}^{COV*} y_{PPS}^{COV*})$ can be obtained if and only if $\xi > \xi_{PPS}$. (Q.E.D.)

Proof of Proposition 3.4: We define $\Delta p_{WSO} = p_{WSO}^* - p_{PPS}^{COV*}$, $\Delta y_{WSO} = y_{WSO}^* - y_{PPS}^{COV*}$, $\Delta\pi_{WSO} = \pi_{WSO}^* - \pi_{PPS}^{COV*}$ and $\Delta WCC_{WSO} = WCC_{WSO}^* - WCC_{PPS}^{COV*}$; we check characteristics of such differences one by one in the following. (i) By substituting optimal decisions, we can obtain that $\Delta p_{WSO} = \frac{\theta(-gk^2+2g\lambda-2t\lambda+2\lambda\xi)}{4\lambda-k^2}$ and $\Delta y_{WSO} = -\frac{k\theta(g+t-\xi)}{s(4\lambda-k^2)}$ are increasing in ξ. When $\xi = t + g\left(\frac{k^2}{2\lambda} - 1\right)$ and $\xi = t + g$, $\Delta p_{WSO} = 0$ and $\Delta y_{WSO} = 0$ can be achieved, respectively; so, $\Delta p_{WSO} > 0$ and $\Delta y_{WSO} > 0$ can be obtained when $\xi > t + g\left(\frac{k^2}{2\lambda} - 1\right)$ and $\xi > t + g$, respectively. (ii) The difference in the optimal profit can be derived as $\Delta\pi_{WSO} = \frac{\theta(fk(g+t-\xi)+s[g^2\theta\lambda+\lambda(t-\xi)(-2+2c+2\beta+t\theta+2\xi-\theta\xi)+g(k^2(-1+\theta)(t-\xi)+2\lambda(-1+c+2t+\beta-t\theta+(-1+\theta)\xi)))]}{-s(4\lambda-k^2)}$ and we have $\frac{\partial\Delta\pi_{WSO}(\theta)}{\partial\theta} > 0$. Moreover, it can be obtained that $\Delta\pi_{WSO}(\theta)$ =0 when $\theta' = \frac{s\lambda\xi^2+[fk-2s(1-c-\beta)\lambda]\xi-(g+t)(fk-s(2-2c-g-t-2\beta)\lambda)}{s(g^2\lambda+g(k^2-2\lambda)(t-\xi)+\lambda(t-\xi)^2)}$. Moreover, it is noticeable that when $s\lambda\xi^2 + [fk - 2s(1 - c - \beta)\lambda]\xi - (g + t)(fk - s(2 - 2c - g - t - 2\beta)\lambda) \leq 0$, the $\theta' \in [0,1]$ always hold. Therefore, we can obtain two cases (a) when $\underline{\xi}^B \leq \xi \leq \overline{\xi}^B \Rightarrow \theta' \in [0,1]$, $\Delta\pi_{WSO}(\theta)\begin{Bmatrix}>\\=\\<\end{Bmatrix}0$ if and only if $\theta\begin{Bmatrix}>\\=\\<\end{Bmatrix}\theta'$; (b) when $\xi < \underline{\xi}^B$ *or* $\xi > \overline{\xi}^B \Rightarrow \theta' > 1$, $\Delta\pi_{WSO}(\theta) < 0$ always holds, where $\underline{\xi}^B$ and $\overline{\xi}^B$ are the two positive roots of equation $s\lambda\xi^2 + [fk - 2s(1 - c - \beta)\lambda]\xi - (g + t)(fk - s(2 - 2c - g - t - 2\beta)\lambda) = 0$.

(iii) Frist, we derive that $\Delta WCC_{PPS} = -\frac{\theta\left[\begin{matrix}(2g^2s\theta(k^2-6\lambda)\lambda+2g(-2fk\lambda+k^4s(-1+\theta)(t-\xi)-4s\lambda^2(-3+3c+4t+\beta-t\theta+(-1+\theta)\xi)+2k^2s\lambda(-1+c+4t-3t\theta+3(-1+\theta)\xi))\\+(t-\xi)(-4fk\lambda+k^4s(-1+\theta)(t-\xi)+2k^2s\lambda(-2+2c+4t-3t\theta-2\xi+3\theta\xi)-4s\lambda^2(-6+6c+4t+2\beta-t\theta+(2+\theta)\xi)))\end{matrix}\right]}{2s(4\lambda-k^2)^2}$

and given $W(\theta) = (2g^2s\theta(k^2 - 6\lambda)\lambda + 2g(-2fk\lambda + k^4s(-1 + \theta)(t - \xi) - 4s\lambda^2(-3 + 3c + 4t + \beta - t\theta + (-1 + \theta)\xi) + 2k^2s\lambda(-1 + c + 4t - 3t\theta + 3(-1 + \theta)\xi)) + (t - \xi)(-4fk\lambda + k^4s(-1 + \theta)(t - \xi) + 2k^2s\lambda(-2 + 2c + 4t - 3t\theta - 2\xi + 3\theta\xi) - 4s\lambda^2(-6 + 6c + 4t + 2\beta - t\theta + (2 + \theta)\xi)))$. It can be obtained that $\frac{\partial W(\theta)}{\partial\theta} = sX(t - \xi)$, and to find the characteristic of $W(\theta)$, that is $\frac{\partial W(\theta)}{\partial\theta} > 0$ when $X(t - \xi) > 0$, otherwise $\frac{\partial W(\theta)}{\partial\theta} \leq 0$. Therefore, we need to consider two separate cases for analysing ΔWCC_{PPS} which depend on $X(t - \xi)$.

(a)$X(t - \xi) > 0 \Rightarrow W(\theta)\begin{Bmatrix}>\\=\\<\end{Bmatrix}0$ if and only if $\theta\begin{Bmatrix}>\\=\\<\end{Bmatrix}\theta'' \Rightarrow \Delta WCC_{PPS}\begin{Bmatrix}<\\=\\>\end{Bmatrix}0$;

(b)$X(t - \xi) < 0 \Rightarrow W(\theta)\begin{Bmatrix}>\\=\\<\end{Bmatrix}0$ if and only if $\theta\begin{Bmatrix}<\\=\\>\end{Bmatrix}\theta'' \Rightarrow \Delta WCC_{PPS}\begin{Bmatrix}<\\=\\>\end{Bmatrix}0$, where $\theta'' = \frac{\left[\begin{matrix}2g\left(2fk\lambda-2k^2s\lambda(-1+c+4t-3\xi)+k^4s(t-\xi)+4s\lambda^2(-3+3c+4t+\beta-\xi)\right)\\+(t-\xi)(4fk\lambda+k^4s(t-\xi)+4k^2s\lambda(1-c-2t+\xi)+8s\lambda^2(-3+3c+2t+\beta+\xi))\end{matrix}\right]}{s(2g^2(k^2-6\lambda)\lambda+2g(k^4-6k^2\lambda+4\lambda^2)(t-\xi)+(k^4-6k^2\lambda+4\lambda^2)(t-\xi)^2))}$. (Q.E.D.)

Proof of Proposition 3.5: Based on Proof of Proposition 3.4, we can obtain that $\Delta\pi_{WSO} < 0$ and $\Delta WCC_{PPS} > 0$ when $\theta'' < \theta < \theta'$. We define that $\underline{N} = \Delta\pi_{WSO} + \Delta WCC_{PPS} = \frac{\theta[A_1(t-\xi)^2 + A_2(t-\xi) + A_3]}{2s(4\lambda-k^2)^2}$, where $A_1 = k^4 s(1-\theta)$, $A_2 = -2f(k^3 - 6k\lambda) - 4s\big[gk^4(-1+\theta) + \lambda\big(-\lambda(-10 + 10c + 6\beta + t(4+\theta) + 6\xi - \theta\xi) + k^2(-2 + 2c + 2t + \beta - t\theta + \theta\xi)\big)\big]$ and $A_3 = -2g(f(k^3 - 6k\lambda) + 2s\lambda[g\theta(k^2 - 5\lambda) - 2\lambda(-5 + 5c + 8t + 3\beta - 3t\theta + 3(-1+\theta)\xi))]$.

(Q.E.D.)

Proof of Lemma 3.4: Similar to approaches to derive optimal decisions for basic models, i.e., Proof of Lemma 3.3, we derive optimal solutions for Case I and Case II which are shown in the main body. Noticeably, to ensure joint concavity of solutions for two cases, we still need $\lambda > \frac{k^2}{4}$. Besides, the D_{WSO}^{EC*} $(p_{WSO}^{EC*}, y_{WSO}^{EC*})$'s first order derivatives w. r. t. β are negative for two cases, and there is D_{WSO}^{EC*} =0 when $\beta_{WSO}^{EC} = \begin{cases} 1 - c - g - \frac{fk}{2s\lambda} - \frac{\hat{t}}{2} & if \xi \geq \hat{t} \\ 1 - c - \frac{fk}{2s\lambda} - \frac{(2g + 3\hat{t} - 2\xi)\xi}{2\hat{t}} & if \xi < \hat{t} \end{cases}$. At last, comparing β_{WSO}^{EC} and β_{PPS}^{COV}, the relationship between them is $\beta_{WSO}^{EC} \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} \beta_{PPS}^{COV}$ if and only if $\xi \begin{Bmatrix} > \\ = \\ < \end{Bmatrix} g + \frac{\hat{t}}{2}$ can be obtained.

(Q.E.D.)

Proof of Proposition 3.6: (i) By comparing optimal prices and employment levels under Model WSO^{EC} and Model PPS, it is straightforward to obtain that $\Delta p_{WSO}^{EC} = p_{WSO}^{EC*} - p_{PPS}^{COV*}$ and $\Delta y_{WSO}^{EC} = y_{WSO}^{EC*} - y_{PPS}^{COV*}$ are increasing in ξ. Moreover, $\Delta p_{WSO}^{EC} = 0$ and $\Delta y_{WSO}^{EC} = 0$ when $\xi = \frac{gk^2 - 2g\lambda + \hat{t}\lambda}{2\lambda}$ and $\xi = \frac{2gk + k\hat{t}}{2k}$, respectively. Therefore, we have $\Delta p_{WSO}^{EC} > 0$ and $\Delta y_{WSO}^{EC} > 0$ when $\xi > \frac{gk^2 - 2g\lambda + \hat{t}\lambda}{2\lambda}$ and $\xi > \frac{2gk + k\hat{t}}{2k}$.

(ii) Define that $\Delta\pi_{WSO}^{EC} = \pi_{WSO}^{EC*} - \pi_{PPS}^{COV*}$, the characteristics of $\Delta\pi_{WSO}^{EC}$ are shown as follows: (a) In Case I, $\Delta\pi_{WSO}^{EC}$ is increasing in ξ and $\Delta\pi_{WSO}^{EC} = 0$ when $\xi = 1 - c - \beta - \frac{fk}{2s\lambda}$. Therefore, $\Delta\pi_{WSO}^{EC}$>0 when $\xi > 1 - c - \beta - \frac{fk}{2s\lambda}$; (b) In Case II, we can derive that $\Delta\pi_{WSO}^{EC} = \frac{-\xi Y^{EC}(\xi)}{4st^2(4\lambda - k^2)}$, where $Y^{EC}(\xi) = -4s\lambda\xi^3 + (4gk^2 s - 8gs\lambda + 12st\lambda)\xi^2 + (4fkt - 6gk^2 st - 4g^2 s\lambda + 12gst\lambda - 5st^2\lambda + 8st(-1 + c + \beta)\lambda)\xi - 4fgkt - 2fkt^2 + 2gk^2 st^2 - 4st^2(-1 + c + \beta)\lambda - 8gst(-1 +$

$c+t+\beta)\lambda$. Given that $\underline{\xi}$ and $\overline{\xi}$ are two possible positive roots of equation $Y^{EC}(\xi)=0$, it can be obtained that $Y^{EC}(\xi)>0 \Rightarrow \Delta\pi_{WSO}^{EC}<0$ if $\underline{\xi}<\xi<\min\{\overline{\xi},\hat{t}\}$, otherwise, $Y^{EC}(\xi)\leq 0 \Rightarrow \Delta\pi_{WSO}^{EC}\geq 0$.

(iii) Define that $\Delta WCC_{WSO}^{EC}=WCC_{WSO}^{EC*}-WCC_{PPS}^{COV*}$, the characteristics of ΔWCC_{WSO}^{EC} are shown in the following two cases. (a) In Case I, we can derive that $\Delta WCC_{WSO}^{EC}=\frac{\lambda(2g+t-2\xi)[4fk+4k^2s-4ck^2s-2gk^2s-k^2st-24s\lambda+24cs\lambda+12gs\lambda+6st\lambda+8s\beta\lambda+(-2k^2s+12s\lambda)\xi]}{4s(k^2-4\lambda)^2}$, $\frac{\partial(2g+t-2\xi)}{\partial\xi}<0$ and $\frac{\partial[4fk+4k^2s-4ck^2s-2gk^2s-k^2st-24s\lambda+24cs\lambda+12gs\lambda+6st\lambda+8s\beta\lambda+(-2k^2s+12s\lambda)\xi]}{\partial\xi}>0$. Moreover, $2g+t-2\xi=0$ and $[4fk+4k^2s-4ck^2s-2gk^2s-k^2st-24s\lambda+24cs\lambda+12gs\lambda+6st\lambda+8s\beta\lambda+(-2k^2s+12s\lambda)\xi]=0$ when $\xi=\frac{2g+t}{2}$ and $\xi=\frac{1}{6}(12-12c-6g-3t-4\beta+\frac{4k(3f+ks\beta)}{s(k^2-6\lambda)})$, respectively. We define $\underline{\xi}^{I}=\min\{\frac{1}{6}\left(12-12c-6g-3\hat{t}-4\beta+\frac{4k(3f+ks\beta)}{s(k^2-6\lambda)}\right),\frac{1}{2}(2g+\hat{t})\}$, $\overline{\xi}^{I}=\max\{\frac{1}{6}\left(12-12c-6g-3\hat{t}-4\beta+\frac{4k(3f+ks\beta)}{s(k^2-6\lambda)}\right)$, so that $\Delta WCC_{WSO}^{EC}>0$ when $max\{\underline{\xi}^{I},\hat{t}\}<\xi<\overline{\xi}^{I}$. (b) In Case II, we can derive that $\Delta WCC_{WSO}^{EC}=\frac{\xi X^{EC}(\xi)}{8st^2(k^2-4\lambda)^2}$, where $X^{EC}(\xi)=-4s(k^4-6k^2\lambda+4\lambda^2)\xi^3+8s[(k^4-6k^2\lambda+4\lambda^2)(g+\hat{t})+\hat{t}\lambda k^2-6\hat{t}\lambda^2]\xi^2+\{8g^2s\lambda(6\lambda-k^2)-12gs\hat{t}(k^4-6k^2\lambda+4\lambda^2)-t\{5k^4s\hat{t}+2k[8f+ks(8-8c-15\hat{t})]\lambda+4s[24-24c-5\hat{t}-8\beta]\lambda^2)\}\xi+\hat{t}\{\hat{t}[k^4s\hat{t}+8k\big(f+ks(1-c-\hat{t})\big)\lambda-16s(3-3c-t-\beta)\lambda^2]+4g[k^4s\hat{t}+4k\big(f+(1-c-2\hat{t})\big)\lambda-8s(3-3c-2\hat{t}-\beta)\lambda^2]\}$. Given that $\underline{\xi}^{II}$ and $\overline{\xi}^{II}$ are two larger roots of equation $X^{EC}(\xi)=-4s(k^4-6k^2\lambda+4\lambda^2)\xi^3+8s[(k^4-6k^2\lambda+4\lambda^2)(g+\hat{t})+\hat{t}\lambda k^2-6\hat{t}\lambda^2]\xi^2+\{8g^2s\lambda(6\lambda-k^2)-12gs\hat{t}(k^4-6k^2\lambda+4\lambda^2)-t\{5k^4s\hat{t}+2k[8f+ks(8-8c-15\hat{t})]\lambda+4s[24-24c-5\hat{t}-8\beta]\lambda^2)\}\xi+\hat{t}\{\hat{t}[k^4s\hat{t}+8k\big(f+ks(1-c-\hat{t})\big)\lambda-16s(3-3c-t-\beta)\lambda^2]+4g[k^4s\hat{t}+4k\big(f+(1-c-2\hat{t})\big)\lambda-8s(3-3c-2\hat{t}-\beta)\lambda^2]\}=0$, if $\lambda\geq\frac{(3+\sqrt{5})k^2}{4}$, $X^{EC}(\xi)>0 \Rightarrow \Delta WCC_{WSO}^{EC}>0$ when $max\{\underline{\xi}^{II},0\}<\xi<\min\{\overline{\xi}^{II},\hat{t}\}$; if $<\frac{(3+\sqrt{5})k^2}{4}$, $X^{EC}(\xi)>0 \Rightarrow \Delta WCC_{WSO}^{EC}>0$ when $0<\xi<\min\{\underline{\xi}^{II},\hat{t}\}\ or\ \overline{\xi}^{II}<\xi<\hat{t}$. (Q.E.D.)

Proof of Lemma 3.5: Deriving the first order condition of optimal profits w. r. t s for three models: Model PPS, Model PPS-C and Model WSO one by one. It can be proved that $\frac{\partial \pi_{PPS}^{\overline{COV}*}}{\partial s} = \frac{f(ks(1-c-\beta)-2f)}{s^3(4\lambda-k^2)} > 0$, $\frac{\partial \pi_{WSO}^{\mathrm{COV}*}}{\partial s} = \frac{f(ks(1-c-\beta-\xi)-2f)}{s^3(4\lambda-k^2)} > 0$ and $\frac{\partial \pi_{WSO}^{*}}{\partial s} = \frac{f(ks(1-c-\beta-\xi-\theta(g+t-\xi))-2f)}{s^3(4\lambda-k^2)} > 0$, which means that the firm sets its sales service level at the maximum value. Due to $C(y,s)$ is increasing in s and $C(y,s) \leq H$, we can see that the optimal s can be achieved when $C(y^*,s) = H$. Before proving (ii) and (iii) of Lemma 3.5, we need to derive optimal decisions for models in Lemma 3.5A. Then for (ii) and (iii), similar to the approach be shown in Lemma 1-3, the threshold of β and relationships among them can be obtained.

Lemma 3.5A: We use the same approach as the one in proving Model PPS and derive the optimal solutions for three models in Table A3-1.

Model PPS: we first derive that $C_{PPS}^{\overline{COV}}(y^*,s) = \frac{(2f+ks(-1+c+\beta))^2\lambda}{2s^2(k^2-4\lambda)^2}$, and $s_{PPS}^{ES-\overline{COV}*}$ can be obtained by solving $C_{PPS}^{\overline{COV}}(y^*,s) = H$; by substituting $s_{PPS}^{ES-\overline{COV}*}$ into $p_{PPS}^{\overline{COV}*}$ and $y_{PPS}^{\overline{COV}*}$, $p_{PPS}^{ES-\overline{COV}*}$ and $y_{PPS}^{ES-\overline{COV}*}$ can be derived. (Q.E.D.)

Table A3-1. Optimal solutions for the endogenous service level case.

Case	Condition	Optimal number of salespeople	Optimal retail price	Optimal sales service level
PPS	$\lambda > \frac{k^2}{4}$	$y_{PPS}^{ES-\overline{COV}*} = \frac{\sqrt{2}H(k^2-4\lambda)-k(-1+c+\beta)\sqrt{H\lambda}}{\sqrt{2}f\lambda}$	$p_{PPS}^{ES-\overline{COV}*} = \frac{1}{2}(1 + c + \beta + \frac{\sqrt{2}Hk}{\sqrt{H\lambda}})$	$s_{PPS}^{ES-\overline{COV}*} = \frac{2f^2\lambda}{\sqrt{2}\sqrt{f^2H(k^2-4\lambda)^2\lambda}-fk(-1+c+\beta)\lambda}$
PPS-C		$y_{PPS}^{ES-COV*} = \frac{\sqrt{H\lambda}(\sqrt{2}k^2\sqrt{H\lambda}-4\sqrt{2}\lambda\sqrt{H\lambda}-k\lambda(-1+c+\beta+\xi))}{\sqrt{2}f\lambda^2}$	$p_{PPS}^{ES-COV*} = \frac{1}{2}(1 + c + \beta + \frac{\sqrt{2}Hk}{\sqrt{H\lambda}} - \xi)$	$s_{PPS}^{ES-COV*} = \frac{2f\lambda}{\sqrt{2}k^2\sqrt{H\lambda}-4\sqrt{2}\lambda\sqrt{H\lambda}-k\lambda(-1+c+\beta+\xi)}$
WSO		$y_{WSO}^{SO*} = \frac{\sqrt{H\lambda}(\sqrt{2}k^2\sqrt{H\lambda}-4\sqrt{2}\lambda\sqrt{H\lambda}-k\lambda M)}{\sqrt{2}f\lambda^2}$	$p_{WSO}^{SO*} = \frac{\sqrt{2}k\sqrt{H\lambda}+\lambda(2(c+\beta+g\theta)-M)}{2\lambda}$	$s_{WSO}^{SO*} = \frac{2f\lambda}{\sqrt{2}k^2\sqrt{H\lambda}-4\sqrt{2}\lambda\sqrt{H\lambda}-k\lambda M}$
Remark: $M = (-1 + c + \beta + g\theta + t\theta + \xi - \theta\xi)$				

Proof of Proposition 3.7 and Proof of Proposition 3.8: We adopt the same approach as the one in Basic Mode and Comparisons and Analysis; we only show the special threshold used in these two propositions as follows.

(i) $p_{WSO}^{ES*}\begin{Bmatrix}>\\=\\<\end{Bmatrix}p_{PPS}^{ES-COV*}$ if $\xi\begin{Bmatrix}>\\=\\<\end{Bmatrix}t-g$; $y_{WSO}^{ES*}>y_{PPS}^{ES-COV*}$ if $\xi\begin{Bmatrix}>\\=\\<\end{Bmatrix}t+g$; $s_{SO}^{ES*}<s_{PPS}^{ES-COV*}$ if $\xi\begin{Bmatrix}<\\=\\>\end{Bmatrix}t+g$;

(ii) Given that $\Delta WCC_{WSO}^{ES}=X^{ES}(\xi)$ and $X^{ES}(\xi)=A_1^{ES}\xi^2+A_2^{ES}\xi+A_3^{ES}$, where $A_1^{ES}=-\theta(2+\theta)\lambda$, $A_2^{ES}=(6\theta\lambda-6c\theta\lambda-2g\theta\lambda-2\beta\theta\lambda+2t(-1+\theta)\theta\lambda+2g\theta^2\lambda-12\sqrt{2}k\sqrt{H\lambda}+6\sqrt{2}k\theta\sqrt{H\lambda})$ and $A_3^{ES}=-6g\theta\lambda+6cg\theta\lambda-6t\theta\lambda+6ct\theta\lambda+2g\beta\theta\lambda+2t\beta\theta\lambda-2gt(-4+\theta)\theta\lambda-t^2(-4+\theta)\theta\lambda+3g^2\theta^2\lambda+12\sqrt{2}k\sqrt{H\lambda}-4\sqrt{2}k(3c+\beta)\sqrt{H\lambda}-6\sqrt{2}gk\theta\sqrt{H\lambda}-6\sqrt{2}kt\theta\sqrt{H\lambda}$. The $root_1$ and $root_2$ are roots of $W^{ES}(\xi)$, they are $root_1=\frac{1}{\theta(2+\theta)\lambda}(-\theta(-3+3c+g+t+\beta-(g+t)\theta)\lambda-6\sqrt{2}k\sqrt{H\lambda}+3\sqrt{2}k\theta\sqrt{H\lambda}+\sqrt{}(\lambda(18Hk^2(-2+\theta)^2+\theta(4g^2\theta^2\lambda+4g^2\theta^3\lambda+4\sqrt{2}k(3(-1+c+g+t)+\beta)\sqrt{H\lambda}+\theta((9c^2+g^2+6g(-3+3t+\beta)+(-3+3t+\beta)^2+6c(3(-1+g+t)+\beta))\lambda-10\sqrt{2}k(3(-1+c+g+t)+\beta)\sqrt{H\lambda})))))\}$ and $root_2=-\frac{1}{\theta(2+\theta)\lambda}(\theta(-3+3c+g+t+\beta-(g+t)\theta)\lambda+6\sqrt{2}k\sqrt{H\lambda}-3\sqrt{2}k\theta\sqrt{H\lambda}+\sqrt{}(\lambda(18Hk^2(-2+\theta)^2+\theta(4g^2\theta^2\lambda+4g^2\theta^3\lambda+4\sqrt{2}k(3(-1+c+g+t)+\beta)\sqrt{H\lambda}+\theta((9c^2+g^2+6g(-3+3t+\beta)+(-3+3t+\beta)^2+6c(3(-1+g+t)+\beta))\lambda-10\sqrt{2}k(3(-1+c+g+t)+\beta)\sqrt{H\lambda})))))$. (Q.E.D.)

Proof of Proposition 3.9: First note that for the WCC-welfare-oriented firm, the optimal solutions are derived by maximizing firm's WCC welfare. By using the same approach as the one in Proof of Lemma 3.1, we can yield the optimal solutions for three cases, i.e., PPS, PPS-C, and WSO as shown in Table A3-2. The condition to ensure concavity is obtained by solving the determinant of Hessian Matrix $H^{WO}=\begin{vmatrix}1-2\alpha & -ks(1-\alpha)\\ -ks(1-\alpha) & s^2(k^2-2\alpha\lambda)\end{vmatrix}=s^2[2(2\alpha-1)\lambda-k^2\alpha^2]>0$ and $1-2\alpha<0$.

Table A3-2. Optimal solutions for WCC-welfare-oriented firm.

Case	Condition	Optimal number of salespeople	Optimal retail price
PPS	$\lambda>\frac{k^2\alpha}{2(2\alpha-1)}$	$y_{PPS}^{WO-\overline{COV}*}=\frac{ks\alpha(R+\alpha)-f(1-\alpha)(1-2\alpha)}{s^2\alpha[2(2\alpha-1)\lambda-k^2\alpha]}$	$p_{PPS}^{WO-\overline{COV}*}=\frac{s\alpha[R(k^2-2\lambda)-2(1-\alpha)\lambda]-fk(1-\alpha)^2}{s\alpha[2(2\alpha-1)\lambda-k^2\alpha]}$
PPS-C	$and\ \alpha>\frac{1}{2}$	$y_{PPS}^{WO-COV*}=\frac{ks\alpha[R+\alpha(1-\xi)]-f(1-\alpha)(1-2\alpha)}{s^2\alpha[2(2\alpha-1)\lambda-k^2\alpha]}$	$p_{PPS}^{WO-COV*}=$

			$\frac{s\alpha[R(k^2-2\lambda)-2\lambda(1-\alpha)(1-\xi)]-fk(1-\alpha)^2}{s\alpha[2(2\alpha-1)\lambda-k^2\alpha]}$
WSO		$y_{WSO}^{WO*}=\frac{ks\alpha[R+\alpha(1-\theta(g+t-\xi)-\xi)]-f(1-\alpha)(1-2\alpha)}{s^2\alpha[2(2\alpha-1)\lambda-k^2\alpha]}$	$p_{WSO}^{WO*}=\frac{s\alpha\begin{bmatrix}R(k^2-2\lambda)-g\alpha\theta(k^2-2\lambda)\\-2(1-\alpha)\lambda(1-t\theta-\xi+\theta\xi)\end{bmatrix}-fk(1-\alpha)^2}{s\alpha[2(2\alpha-1)\lambda-k^2\alpha]}$
Remark: $R=(1-\alpha)\beta-\alpha c$			

By substituting the above optimal solutions into demand functions, we can get the optimal demand in each case are: $D_{PPS}^{WO-\overline{COV}*}=\frac{fk(1-\alpha)+2s[\beta+\alpha(1-c-\beta)]\lambda}{s[2(2\alpha-1)\lambda-k^2\alpha]}$, $D_{PPS}^{WO-COV*}=\frac{fk(1-\alpha)+2s\lambda[\beta+\alpha(1-c-\beta-\xi)]}{s[2(2\alpha-1)\lambda-k^2\alpha]}$, and $D_{WSO}^{WO*}=\frac{fk(1-\alpha)+2s\lambda(\beta+\alpha(1-c-\beta-\theta(g+t-\xi)-\xi))}{s(2(2\alpha-1)\lambda-k^2\alpha)}$, respectively. To ensure positive demand, we have:

- For case PPS, when $\frac{1}{2}<\alpha<1$, $D_{PPS}^{WO-\overline{COV}*}>0$ always hold; while when $\alpha\geq 1$, $D_{PPS}^{WO-\overline{COV}*}\geq 0$ if and only if $\beta\leq\beta_{PPS}^{WO-\overline{COV}}=\frac{2s\lambda\alpha(1-c)-fk(\alpha-1)}{2s\lambda(\alpha-1)}$.
- For case PPS-C, when $\frac{1}{2}<\alpha<1$, $D_{PPS}^{WO-COV*}>0$ always hold; while when $\alpha\geq 1$, $D_{PPS}^{WO-COV*}>0$ if and only if $\beta\leq\beta_{PPS}^{WO-COV}=\frac{2s\alpha\lambda(1-c-\xi)-fk(\alpha-1)}{2s(\alpha-1)\lambda}$.
- For case WSO, when $\frac{1}{2}<\alpha<1$, $D_{WSO}^{WO*}>0$ always hold; while when $\alpha\geq 1$, $D_{WSO}^{WO*}>0$ if and only if $\beta\leq\beta_{WSO}^{WO}=\frac{2s\alpha\lambda(1-c-\theta(g+t-\xi)-\xi)-fk(\alpha-1)}{2s(\alpha-1)\lambda}$.

By comparing the thresholds for β derived in this case with the ones in the basic model (i.e., $\beta_{PPS}^{\overline{COV}}=1-c-\frac{fk}{2s\lambda}$, $\beta_{PPS}^{COV}=1-c-\xi-\frac{fk}{2s\lambda}$, and $\beta_{WSO}=1-c-(1-\theta)\xi-\theta(t+g)-\frac{kf}{2s\lambda}$), we can easily find that $\beta_{PPS}^{WO-\overline{COV}}>\beta_{PPS}^{\overline{COV}}$, $\beta_{PPS}^{WO-COV}>\beta_{PPS}^{COV}$, and $\beta_{WSO}^{WO}>\beta_{WSO}$. We hence infer that WCC-welfare-oriented firm is less likely to lose all the business than profit-oriented firm. (Q.E.D.)

Proof of Proposition 3.10: By using the same comparison method as the one we adopted in Proof of Proposition 3.6, we can yield the results shown in Proposition 3.10. (Q.E.D.)

Proof of Proposition 4.1: We first derive the conditions of concavity as follows. In Model C, the optimal price ($p_C^*\,|\,s_C$) and quality ($q_C^*\,|\,s_C$) can be obtained from solving the first order condition $\frac{\partial\Pi_C}{\partial p}=\frac{k+q\xi+\varepsilon[1+s_C-(1-q)\tau]}{\varepsilon}=0$ and $\frac{\partial\Pi_C}{\partial q}=\frac{\theta[(p-s_C-1)\xi+(p\varepsilon-k)\tau)-q(\varepsilon\lambda+2\theta\xi\tau)}{\varepsilon}=0$, and then substituting with each other. To ensure concavity, we derive the Hessian Matrix

$$H=\begin{bmatrix} -2\theta & \theta(\frac{\xi}{\varepsilon}+\tau) \\ \theta(\frac{\xi}{\varepsilon}+\tau) & -\lambda-\frac{2\theta\xi\tau}{\varepsilon} \end{bmatrix}=\frac{\theta[2\lambda\varepsilon^2-\theta(\xi-\varepsilon\tau)^2]}{\varepsilon^2}>0\,.$$

Then, we substitute $p_C^* \mid s_C$ and $q_C^* \mid s_C$ into SW_C and take the first and second order derivatives. We find that when $\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda>0$, SW_C is concave in s_C and the optimal subsidy s_C^* can be derived by solving $\frac{\partial SW_C}{\partial s}=0$.

We hence notice that the optimal solutions can be obtained under two conditions:

$$\frac{\theta[2\lambda\varepsilon^2-\theta(\xi-\varepsilon\tau)^2]}{\varepsilon^2}>0\text{, and} \tag{A4.1}$$

$$\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda>0\,. \tag{A4.2}$$

From (A4.1), we have $\lambda>\frac{\theta(\tau\varepsilon-\xi)^2}{2\varepsilon^2}$. From (A4.2), when $2\alpha+\beta-4\eta\ge 0\Leftrightarrow\alpha\ge\frac{4\eta-\beta}{2}$, we have $\lambda<\frac{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]}{(2\alpha+\beta-4\eta)\varepsilon^2}$, where $\frac{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]}{(2\alpha+\beta-4\eta)\varepsilon^2}\le\frac{\theta(\tau\varepsilon-\xi)^2}{2\varepsilon^2}$. Thus, it is impossible to satisfy (A4.1) and (A4.2) at the same time; while since $2\alpha+\beta-4\eta<0\Leftrightarrow\alpha<\frac{4\eta-\beta}{2}$, we have $\lambda>\frac{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]}{(2\alpha+\beta-4\eta)\varepsilon^2}$, where $\frac{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]}{(2\alpha+\beta-4\eta)\varepsilon^2}>\frac{\theta(\tau\varepsilon-\xi)^2}{2\varepsilon^2}$.

To summarize, conditions $\alpha<\bar{\alpha}$ and $\lambda>\underline{\lambda}$ should be satisfied for Models C and M, where $\bar{\alpha}=(4\eta-\beta)/2$ and $\underline{\lambda}=\frac{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]}{(2\alpha+\beta-4\eta)\varepsilon^2}$.

Then, please note that $q_O^*=q_i^* \mid (s_i=0)$ and $p_O^*=p_i^* \mid (s_i=0)$, where *i=C or M*. we thus find $\frac{\partial q_i^* \mid s_i}{\partial s_i}=\frac{\varepsilon\theta(\tau\varepsilon-\xi)}{2\lambda\varepsilon^2-\theta(\xi-\varepsilon\tau)^2}>0$ and $\frac{\partial p_C^* \mid s_C}{\partial s_C}=\frac{\lambda\varepsilon^2+\theta\xi(\varepsilon\tau-\xi)}{2\lambda\varepsilon^2-\theta(\xi-\varepsilon\tau)^2}>0$, while $\frac{\partial p_M^* \mid s_M}{\partial s_M}=\frac{\varepsilon[\theta\tau(\varepsilon\tau-\xi)-\varepsilon\lambda]}{2\lambda\varepsilon^2-\theta(\xi-\varepsilon\tau)^2}>0$ if and only if $\lambda<\frac{\theta\tau(\tau\varepsilon-\xi)}{\varepsilon}$. Since $s_i>0$, we can infer $q_i^*>q_O^*$, *and* $p_C^*>p_O^*$*; while* $p_M^*<p_O^*$ *if and only if* $\lambda>\frac{\theta\tau(\tau\varepsilon-\xi)}{\varepsilon}$. We let $\hat{\lambda}=\frac{\theta\tau(\tau\varepsilon-\xi)}{\varepsilon}$ and yield

$\frac{\partial \hat{\lambda}}{\partial \tau} = \frac{\theta(2\tau\varepsilon - \xi)}{\varepsilon} > 0$ (Note that, to ensure $D_i^* > 0$ and $q_i^* > 0$, we have $\tau\varepsilon - \xi > 0$). By using the same method, we obtain $\frac{\partial D_i \mid s_i}{\partial s_i} = \frac{\epsilon^2\theta\lambda}{2\lambda\varepsilon^2 - \theta(\xi - \varepsilon\tau)^2} > 0$, $\frac{\partial SC_i \mid s_i}{\partial s_i} = \frac{\varepsilon^3\lambda^2\theta(\varepsilon - k + \varepsilon s_i)}{[2\lambda\varepsilon^2 - \theta(\xi - \varepsilon\tau)^2]^2} > 0$, $\frac{\partial R_i \mid s_i}{\partial s_i} = \frac{2\varepsilon^2\theta^2\lambda\tau(\xi - \varepsilon\tau)(\varepsilon - k + \varepsilon s_i)}{[2\lambda\varepsilon^2 - \theta(\xi - \varepsilon\tau)^2]^2} < 0$ and $\frac{\partial \Pi_i \mid s_i}{\partial s_i} = \frac{\varepsilon\lambda\theta(\varepsilon - k + \varepsilon s_i)}{2\lambda\varepsilon^2 - \theta(\xi - \varepsilon\tau)^2} > 0$, which imply that $D_i^* > D_O^*$, $CS_i^* > CS_O^*$, $R_i^* < R_O^*$ and $\prod_i^* > \prod_O^*$. (Q.E.D.)

Proof of Proposition 4.2: First, by observing the optimal results derived in Chapter 4.4, we can easily find that $s_C^* = s_M^* = s^*$, $\prod_C^* = \prod_M^*$, $CS_C = CS_M$, $R_C = R_M$, and $SW_C - SW_M = \eta(F_M - F_C)$. Then, by substituting $s_i^* = s^*$ into $p_i^* \mid s_i$ and $q_i^* \mid s_i$, it is obvious that $q_C^* = q_M^*$ and $p_C^* - p_M^* = s^*$. (Q.E.D.)

Proof of Proposition 4.3: First, recall that the conditions $\lambda > \frac{\theta(\tau\varepsilon - \xi)[(\alpha - 2\eta)(\tau\varepsilon - \xi) - 2\tau\gamma\varepsilon]}{(2\alpha + \beta - 4\eta)\varepsilon^2}$ and $\alpha < \frac{4\eta - \beta}{2}$ must be satisfied during the analysis. Then, we can find: $\frac{\partial \prod_i^*}{\partial \theta} > 0$, $\frac{\partial CS_i^*}{\partial \theta} > 0$, and

$$\frac{\partial SW_i^*}{\partial \theta} = \frac{\varepsilon^2\eta^2\lambda^2(2\alpha + \beta - 4\eta)(k - \varepsilon)^2}{2\{\theta(\tau\varepsilon - \xi)[(\alpha - 2\eta)(\tau\varepsilon - \xi) - 2\tau\gamma\varepsilon] - (2\alpha + \beta - 4\eta)\varepsilon^2\lambda\}^2} > 0.$$ (Q.E.D.)

Proof of Proposition 4.4: Before we proceed to prove Propositions 4.4-4.7, we use the same approach in Proof of Proposition 4.1 and derive the optimal solutions for the dishonest case in Table A4-4.

By comparing Case A with the basic model, we have $\frac{\hat{s}_M^{A*}}{s_M^*} = \varepsilon < 1 \Rightarrow \hat{s}_M^{A*} < s_M^*$. Then, substituting $\hat{s}_M^{A*} = \varepsilon s_M^*$ into the optimal solutions yields $\hat{q}_M^{A*} = q_M^*$, $\hat{p}_M^{A*} = p_M^*$, $\hat{CS}_M^{A*} = CS_M^*$, $\hat{R}_M^{A*} = R_M^*$, $\hat{\prod}_M^{A*} = \prod_M^*$, and $\hat{SW}_M^A = SW_M$. (Q.E.D.)

Table A4-4. Equilibrium solutions for different Models under dishonest cases.

Cases	**Equilibrium solutions** (The conditions $\alpha < \bar{\alpha}$ and $\lambda > \underline{\lambda}$ are satisfied)

Case A	$\hat{s}_M^{A*} = k-\varepsilon-\frac{[\eta(k-\varepsilon)][2\lambda\varepsilon^2-\theta(\tau\varepsilon-\xi)^2]}{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda}$, $\hat{q}_M^{A*} = \frac{\theta(\tau\varepsilon-\xi)(\varepsilon-k+\hat{s}_M^{A*})}{2\varepsilon^2\lambda-\theta(\tau\varepsilon-\xi)^2}$, $\hat{p}_M^{A*} = \frac{\varepsilon+k-\hat{s}_M^{A*}}{2\varepsilon}+\frac{\theta(\tau\varepsilon-\xi)(\tau\varepsilon+\xi)(\varepsilon-k+\hat{s}_M^{A*})}{2\varepsilon[2\varepsilon^2\lambda-\theta(\tau\varepsilon-\xi)^2]}$, $\hat{\Pi}_M^{A*} = \frac{\theta\lambda\eta^2(k-\varepsilon)^2[2\lambda\varepsilon^2-\theta(\tau\varepsilon-\xi)^2]}{2\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}^2}$, and $\hat{SW}_M^{A*} = \frac{\theta\lambda\eta^2(k-\varepsilon)^2}{2\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}}-\gamma r-\eta F_M$.
Case NA	$\hat{s}_M^{NA*} = s_M^*$, $\hat{q}_M^{NA*} = q_M^*$, $\hat{p}_M^{NA*} = p_M^*$, $\hat{\Pi}_M^{NA*} = \hat{p}_M^{NA*}D_M^{NA}+\hat{s}_M^{NA*}Q_M^{NA}-(k+\xi\hat{q}_M^{NA*})Q_M^{NA}-\frac{\lambda(\hat{q}_M^{NA*})^2}{2}$, and $\hat{SW}_M^{NA*} = \alpha\hat{\Pi}_M^{NA*}+\beta K_M^{NA}-\gamma R_M^{NA}-\eta(\hat{s}_M^{NA*}Q_M^{NA}+F_M)$.
Case BNA	$\hat{s}_M^{BNA*} = \frac{k}{\varepsilon}-1+c_{BNA}-\frac{[\eta(k-(1-c_{BNA})\varepsilon)][2\lambda\varepsilon^2-\theta(\tau\varepsilon-\xi)^2]}{\varepsilon\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}}$, $\hat{q}_M^{BNA*} = \frac{\theta(\tau\varepsilon-\xi)[(1-c_{BNA})\varepsilon-k+\varepsilon\hat{s}_M^{BNA*}]}{2\varepsilon^2\lambda-\theta(\tau\varepsilon-\xi)^2}$, $\hat{p}_M^{BNA*} = \frac{(1+c_{BNA})\varepsilon+k-\varepsilon\hat{s}_M^{BNA*}}{2\varepsilon}+\frac{\theta(\tau\varepsilon-\xi)(\tau\varepsilon+\xi)[(1-c_{BNA})\varepsilon-k+\varepsilon\hat{s}_M^{BNA*}]}{2\varepsilon[2\varepsilon^2\lambda-\theta(\tau\varepsilon-\xi)^2]}$, $\hat{\Pi}_M^{BNA*} = \frac{\theta\lambda[\eta(k-\varepsilon(1-c_{BNA}))]^2[2\lambda\varepsilon^2-\theta(\tau\varepsilon-\xi)^2]}{2\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}^2}-F_{BNA}$, and $\hat{SW}_M^{BNA*} = \frac{\theta\lambda[\eta(k-(1-c_{BNA})\varepsilon)]^2}{2\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}}-\gamma r-\eta F_M-\alpha F_{BNA}$.

Proof of Proposition 4.5: In Case NA, the optimal decisions are the same with the ones in basic model, thus we have $\hat{CS}_M^{NA*} = CS_M^* = \theta(1-p_M^*+xs_M^*+\tau q_M^*)^2/2$ and $\hat{R}_M^{NA*} = R_M^* = [1-\theta(1-p_M^*+xs_M^*+\tau q_M^*)]\tau + \theta(1-p_M^*+xs_M^*+\tau q_M^*)(\tau-\tau q_M^*)$. However, the optimal profit and social welfare are different. Specifically, we have $\hat{\Pi}_M^{NA*}-\Pi_M^* = s_M^*(\frac{D_M}{\varepsilon}-D_M)>0$ and $\hat{SW}_M^{NA*}-SW_M^* = (\alpha-\eta)s_M^*(\frac{D_M}{\varepsilon}-D_M)$. Thus, we can get $\hat{\Pi}_M^{NA*}>\Pi_M^*$, and $\hat{SW}_M^{NA*}>SW_M^*$ if and only if $\alpha>\eta$. (Q.E.D.)

Proof of Proposition 4.6: First, by comparing consumer surplus under NA and BNA cases, we have

$\hat{C}S_M^{BNA*} - \hat{C}S_M^{NA*} = -\frac{c_{BNA}\varepsilon^3[(2-c_{BNA})\varepsilon - 2k]\eta^2\lambda^2\theta}{2\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}^2} < 0 \Leftrightarrow \hat{C}S_M^{BNA*} < \hat{C}S_M^{NA*}$, and

$\hat{R}_M^{BNA*} - \hat{R}_M^{NA*} = \frac{c_{BNA}\varepsilon^3[(2-c_{BNA})\varepsilon - 2k]\eta^2\theta^2\lambda\tau(\tau\varepsilon-\xi)}{\{\theta(\tau\varepsilon-\xi)[(\alpha-2\eta)(\tau\varepsilon-\xi)-2\tau\gamma\varepsilon]-(2\alpha+\beta-4\eta)\varepsilon^2\lambda\}^2} > 0 \Leftrightarrow \hat{R}_M^{BNA*} > \hat{R}_M^{NA*}$.

Then, for the manufacturer's profit, we have $\frac{\partial(\hat{\Pi}_M^{BNA*} - \hat{\Pi}_M^{NA*})}{\partial c_{BNA}} < 0$ and $(\hat{\Pi}_M^{BNA*} - \hat{\Pi}_M^{NA*})\big|(c_{BNA}=0) = s_M^*(D_M - \frac{D_M}{\varepsilon}) - F_{BNA} < 0$. We hence infer that $\hat{\Pi}_M^{BNA*} < \hat{\Pi}_M^{NA*}$.

Finally, in terms of social welfare, we have $\frac{\partial(\hat{S}W_M^{BNA*} - \hat{S}W_M^{NA*})}{\partial c_{BNA}} < 0$ and $(\hat{S}W_M^{BNA*} - \hat{S}W_M^{NA*})\big|(c_{BNA}=0) = (\alpha-\eta)s_M^*(D_M - \frac{D_M}{\varepsilon}) - F_{BNA}$. Thus, $\hat{S}W_M^{BNA*} > \hat{S}W_M^{NA*}$ if and only if $F_{BNA} < (\eta-\alpha)s_M^*(\frac{D_M}{\varepsilon} - D_M)$. Note that we have $\eta > \alpha$ in Case BNA, so $(\alpha-\eta)s_M^*(D_M - \frac{D_M}{\varepsilon})$ is always positive. (Q.E.D.)

Proof of Proposition 4.7: Recall that only when $\eta > \alpha$, the MSC has the incentive to use blockchain, thus, we need compare case NA with case BNA under the condition $\eta > \alpha$. Then, we can have $\frac{\partial\Delta\hat{C}S_M}{\partial k} > 0$, $\frac{\partial\Delta\hat{R}_M}{\partial k} < 0$, $\frac{\partial\Delta\hat{\Pi}_M}{\partial k^2} < 0$, and $\frac{\partial\Delta\hat{S}W_M}{\partial k^2} > 0$. (Q.E.D.)

Proof of Proposition 4.8: First, by using the same approach in Proof of Proposition 4.1, we can obtain the optimal solutions for the controlled price case in Table A4-5.

Table A4-5. Equilibrium solutions for different Models under controlled price.

Models	**Equilibrium solutions (*q** and *s**)**
Model OG	$q_{OG}^* = \frac{\theta[(\varepsilon p_0 - k)\tau - \xi(1-p_0)]}{\varepsilon\lambda + 2\theta\xi\tau}$
Model CG	When $\varepsilon[\varepsilon\lambda(2\eta-\beta)+(2\gamma+4\eta-\beta)\theta\xi\tau](\varepsilon\lambda+\theta\xi\tau)-\alpha\theta\xi^2(\varepsilon\lambda+2\theta\xi\tau) > 0$,

	$q_{CG}^* = \dfrac{\theta\{(\varepsilon p_0 - k)[\varepsilon\tau(\varepsilon\lambda+\theta\xi\tau)(2\eta-\beta)+\xi[\varepsilon\theta\tau^2(\gamma+\eta)-\alpha(\varepsilon\lambda+2\theta\xi\tau)]]-(1-p_0)(\varepsilon\lambda+\theta\xi\tau)\varepsilon\eta\xi\}}{\varepsilon[\varepsilon\lambda(2\eta-\beta)+(2\gamma+4\eta-\beta)\theta\xi\tau](\varepsilon\lambda+\theta\xi\tau)-\alpha\theta\xi^2(\varepsilon\lambda+2\theta\xi\tau)}$ and $s_{CG}^* = \dfrac{\begin{array}{c}(\varepsilon p_0 - k)\{\alpha(\varepsilon\lambda+\theta\xi\tau)(\varepsilon\lambda+2\theta\xi\tau)+\varepsilon\theta\tau^2[\varepsilon\lambda(\beta+\gamma-\eta)+\theta\xi\tau(\beta-2\eta)]\}+\\(1-p_0)\{(\varepsilon\lambda+2\theta\xi\tau)[\varepsilon^2\lambda(\beta-\eta)+\alpha\theta\xi^2]-\varepsilon\theta\xi\tau[2\gamma\varepsilon\lambda+\varepsilon\eta\lambda-(\beta-2\gamma-2\eta)\theta\xi\tau]\}\end{array}}{\varepsilon[\varepsilon\lambda(2\eta-\beta)+(2\gamma+4\eta-\beta)\theta\xi\tau](\varepsilon\lambda+\theta\xi\tau)-\alpha\theta\xi^2(\varepsilon\lambda+2\theta\xi\tau)}$
Model MG	When $(\varepsilon\lambda+2\theta\xi\tau)(2\eta-\alpha)-\varepsilon\theta\tau^2(\beta+2\gamma)>0$ $q_{MG}^* = \dfrac{(\varepsilon p_0 - k)\eta\theta\tau^2-(1-p_0)\{(\varepsilon\lambda+2\theta\xi\tau)(\eta-\alpha)-\theta\tau[(\beta+\gamma)\varepsilon\tau-\xi\eta]\}}{\tau[(\varepsilon\lambda+2\theta\xi\tau)(2\eta-\alpha)-\varepsilon\theta\tau^2(\beta+2\gamma)]}$ and $s_{MG}^* = \dfrac{\begin{array}{c}(\varepsilon p_0 - k)\theta\tau^2[\varepsilon\theta\tau^2(\beta+2\gamma)-(\varepsilon\lambda+2\theta\xi\tau)(\eta-\alpha)]-\\(1-p_0)\{(\varepsilon\lambda+2\theta\xi\tau)(\varepsilon\lambda+\theta\xi\tau)(\eta-\alpha)-\varepsilon\theta\tau^2[(\beta+\gamma)\varepsilon\lambda+\beta\theta\xi\tau]\}\end{array}}{\varepsilon\theta\tau^2[(\varepsilon\lambda+2\theta\xi\tau)(2\eta-\alpha)-\varepsilon\theta\tau^2(\beta+2\gamma)]}$

First, please note that $q_{OG}^* = q_i^* \mid (s_i = 0)$ and $p_{OG}^* = p_i^* \mid (s_i = 0)$, where *i=CG or MG*. Since we have $\dfrac{\partial q_{CG}^*}{\partial s_{CG}} = -\dfrac{\theta\xi}{\varepsilon\lambda+2\theta\xi\tau} < 0$ and $\dfrac{\partial q_{MG}^*}{\partial s_{MG}} = \dfrac{\varepsilon\theta\tau}{\varepsilon\lambda+2\theta\xi\tau} > 0$, we can infer that $q_{CG}^* < q_{OG}^*$ *and* $q_{MG}^* > q_{OG}^*$. Then, in terms of consumer surplus, we have $\dfrac{\partial CS_{CG}^*}{\partial s_{CG}} = \dfrac{\theta(\varepsilon\lambda+\theta\xi\tau)[\theta\tau(\xi-p\xi-k\tau)+\varepsilon(\lambda-p\lambda+p\theta\tau^2)+(\varepsilon\lambda+\theta\xi\tau)s_{CG}]}{(\varepsilon\lambda+2\theta\xi\tau)^2} > 0$ and $\dfrac{\partial CS_{MG}^*}{\partial s_{MG}} = \dfrac{\varepsilon\theta^2\tau^2[\theta\tau(\xi-p\xi-k\tau)+\varepsilon(\lambda-p\lambda+p\theta\tau^2)+\varepsilon\theta\tau^2 s_{MG}]}{(\varepsilon\lambda+2\theta\xi\tau)^2} > 0$ (noting that D_i^* should be positive).

Thus, we infer that $CS_i^* > CS_{OG}^*$, where *i=CG or MG*. Finally, exploring the manufacturer's profit, we have $\dfrac{\partial \Pi_{MG}^*}{\partial s_{MG}} = \dfrac{\theta[\theta\tau(\xi-p\xi-k\tau)+\varepsilon(\lambda-p\lambda+p\theta\tau^2)+\varepsilon\theta\tau^2 s_{MG}]}{\varepsilon\lambda+2\theta\xi\tau} > 0$ and $\dfrac{\partial \Pi_{CG}^*}{\partial s_{CG}} = \dfrac{\theta[p\varepsilon^2\lambda+\theta\xi^2-p\theta\xi^2+p\varepsilon\theta\xi\tau-k(\varepsilon\lambda+\theta\xi\tau)+\theta\xi^2 s_{CG}]}{\varepsilon(\varepsilon\lambda+2\theta\xi\tau)}$ which is positive if and only if $s_{CG}^* > \dfrac{(k-p_0\varepsilon)(\varepsilon\lambda+\theta\xi\tau)-\theta\xi^2(1-p_0)}{\theta\xi^2}$. We hence have $\prod_{MG}^* > \prod_{OG}^*$, *while* $\prod_{CG}^* > \prod_{OG}^*$ if and only if $s_{CG}^* > \dfrac{(k-p_0\varepsilon)(\varepsilon\lambda+\theta\xi\tau)-\theta\xi^2(1-p_0)}{\theta\xi^2}$. (Q.E.D.)

Proof of Proposition 5.1. (i) In Case AA, from Equation (5.3), we have $SW_2^{AA}(q_2|\mu_2, q_1) = E\left[\left(v-\gamma-r\left(1-\left(1-G(t)\right)e_A\right)\right)\min(D_2, q_1+q_2)+(-r)(q_1+q_2-D_2)^- -(w_A+c)q_2 - h(q_1+q_2-D_2)^+\right]$. Maximizing $SW_2^{AA}(q_2|\mu_2, q_1)$ over q_2 (i.e., letting $\frac{dSW_2^{AA}(q_2|\mu_2,q_1)}{dq_2}=0$) yields the optimal order quantity in Stage 2:

$$q_2^{AA*} = \max\{0, \mu_2[1-\gamma+r\left(1-G(t)\right)e_A]+\sigma_2\Phi^{-1}(s)-q_1\}, \tag{A5.1}$$

where $s=\frac{1-2(\gamma+w_A+c-r(1-G(t))e_A)}{1+2(h-\gamma+r(1-G(t))e_A)}$. From (A5.1) we can get $q_2^{AA*}>0$ when $\mu_2[1-\gamma+r\left(1-G(t)\right)e_A]+\sigma_2\Phi^{-1}(s)-q_1>0 \rightarrow \mu_2>\frac{q_1-\sigma_2\Phi^{-1}(s)}{1-\gamma+r\left(1-G(t)\right)e_A}$ and $q_2^{AA*}=0$ when $\mu_1 \le \frac{q_1-\sigma_2\Phi^{-1}(s)}{1-\gamma+r\left(1-G(t)\right)e_A}$. (ii) First, we have $\frac{ds}{de_A}=\frac{4(1-G(t))r(h+w_A+c)}{(1+2h-2\gamma+2(1-G)re_A)^2}>0$ and $\frac{ds}{dr}=\frac{4(1-G(t))e_A(h+w_A+c)}{(1+2h-2\gamma+2(1-G)re_A)^2}>0$. Hence, the numerator of $\bar{\mu}^{UA}$ is decreasing in e_A and r. Meanwhile, we have $\frac{d(1-\gamma+r\left(1-G(t)\right)e_A)}{de_A}=r\left(1-G(t)\right)>0$ and $\frac{d(1-\gamma+r\left(1-G(t)\right)e_A)}{dr}=e_A\left(1-G(t)\right)>0$, which means that the denominator of $\bar{\mu}^{AA}$ is increasing in e_A and r. Consequently, we obtain that $\bar{\mu}^{AA}$ is decreasing in e_A and r. (Q.E.D.)

Proof of Lemma 5.1. (i) Recall that we have $K_A=\frac{1}{2}-\gamma-r[1-\left(1-G(t)\right)e_A]+h+r$ and $m_A=\mu_2(1-\gamma+r\left(1-G(t)\right)e_A)$. We first get the closed-form expression for $E[SW_2^{AA}(q_2^{AA*}=0|\mu_2,q_1)]$ and $E[SW_2^{AA}(q_2^{AA*}>0|\mu_2,q_1)]$ as follows. Note that $\int_{-\infty}^{+\infty} x_2 f(x_2)dx_2=m_A$ and $\psi(a)=\int_a^{\infty}(x-a)d\Phi(x)$.

$E[SW_2^{AA}(q_2^{AA*}=0|\mu_2,q_1)]$

$$\begin{aligned}&=\left[\frac{1}{2}-\gamma-r\left(1-\left(1-G(t)\right)e_A\right)\right]m_A-\int_{q_1}^{\infty}[v-\gamma-r\left(1-\left(1-G(t)\right)e_A\right)]x_2 f(x_2)dx_2\\&+\int_{q_1}^{\infty}[v-\gamma-r\left(1-\left(1-G(t)\right)e_A\right)]q_1 f(x_2)dx_2-\int_{q_1}^{\infty}r(x_2-q_1)f(x_2)dx_2-(w_A+c)q_2\\&+(-h)(q_1-m_A)+\int_{q_1}^{\infty}(-h)(x_2-q_1)f(x_2)dx_2\end{aligned}$$

$$= \left[\frac{1}{2} - \gamma - r\big(1 - \big(1 - G(t)\big)e_A\big)\right] m_A - (-h)(m_A - q_1)$$
$$- \left[\frac{1}{2} - \gamma - r\big(1 - \big(1 - G(t)\big)e_A\big) - (-h) + r\right] \sigma_2 \psi\left(\frac{q_1 - m_A}{\sigma_2}\right)$$
$$= K_A \left[m_A - \sigma_2 \psi\left(\frac{q_1 - m_A}{\sigma_2}\right)\right] - r m_A - h q_1.$$

Similarly, we have $E[SW_2^{AA}(q_2^{AA*} > 0|\mu_2, q_1)] = (K_A - r)m_A - (h + w_A + c)[m_A + \sigma_2 \Phi^{-1}(s)] - K_A \sigma_2 \psi\big(\Phi^{-1}(s)\big) + (w_A + c)q_1$.

Then, we prove the strict concavity of $E[SW_1^{AA}(q_1|\mu_1, q_1)]$ by checking the second-order condition. To simplify notation, we define $z_A = \frac{q_0 - \sigma_2 \Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_A}$. Differentiating $E[SW_1^{AA}(q_1|\mu_1, q_1)$ with respect to q_1 yields:

$$\frac{dE[SW_1^{AA}(q_1|\mu_1, q_1)}{dq_1}$$
$$= \frac{E\big[SW_2^{AA}\big(q_2^{AA*} = 0\big|\mu_2, q_1\big)\big] f(\mu_2)}{1 - \gamma + r\big(1 - G(t)\big)e_A}|_{\mu_2 = z_A} + \int_{-\infty}^{z_A} \frac{dE[SW_2^{AA}\big(q_2^{AA*} = 0\big|\mu_2, q_1\big)] f(\mu_2)}{dq_1} d\mu_2$$
$$- \frac{E\big[SW_2^{AA}\big(q_2^{AA*} > 0\big|\mu_2, q_1\big)\big] f(\mu_2)}{1 - \gamma + r\big(1 - G(t)\big)e_A}|_{\mu_2 = z_A} + \int_{z_A}^{\infty} \frac{dE\big[SW_2^{AA}\big(q_2^{AA*} > 0\big|\mu_2, q_1\big)\big] f(\mu_2)}{dq_1} d\mu_2 - w_A .$$

Notice that $\frac{E\left[SW_2^{AA}\left(q_2^{AA*} = 0\middle|\mu_2, q_1\right)\right] f(\mu_2)}{1-\gamma+r(1-G(t))e_A}|_{\mu_2 = z_A} = \frac{E\left[SW_2^{AA}\left(q_2^{AA*} > 0\middle|\mu_2, q_1\right)\right] f(\mu_2)}{1-\gamma+r(1-G(t))e_A}|_{\mu_2 = z_A}$, hence,

$$\frac{dE[SW_1^{AA}(q_1|\mu_1, q_1)}{dq_1}$$
$$= \int_{-\infty}^{z_A} \frac{dE[SW_2^{AA}(q_2^{AA*} = 0|\mu_2, q_1)] f(\mu_2)}{dq_1} d\mu_2$$
$$+ \int_{z_A}^{\infty} \frac{dE[SW_2^{AA}(q_2^{AA*} > 0|\mu_2, q_1)] f(\mu_2)}{dq_1} d\mu_2 - w_A$$
$$= \int_{-\infty}^{z_A} \left[K_A - h - K_A \Phi\left(\frac{q_1 - m_A}{\sigma_2}\right)\right] f(\mu_2)\, d\mu_2 + \int_{z_A}^{\infty} (w_A + c) f(\mu_2)\, d\mu_2 - w_A$$
$$= \int_{-\infty}^{z_A} [K_A - h - w_A - c] f(\mu_2)\, d\mu_2 + \int_{-\infty}^{\infty} (w_A + c) f(\mu_2)\, d\mu_2$$
$$- K_A \int_{-\infty}^{z_A} \left[\Phi\left(\frac{q_1 - m_A}{\sigma_2}\right)\right] f(\mu_2)\, d\mu_2 - w_A .$$

After standardizing with $\lambda = \frac{\mu_2 - \mu_1}{\sqrt{d_1^2/(d_1+\delta)}}$, we can have

$$\frac{dE[SW_1^{AA}(q_1|\mu_1,q_1)}{dq_1}$$

$$= -K_A \int_{-\infty}^{\frac{z_A-\mu_0}{\sqrt{\frac{d_1^2}{d_1+\delta}}}} \left[\Phi\left(\frac{q_1-m_A}{\sigma_2}\right)\right]\varphi(\lambda)d\lambda + (K_A-h-w_A-c)\Phi\left(\frac{z_A-\mu_0}{\sqrt{\frac{d_1^2}{d_1+\delta}}}\right) + c$$

$$= -K_A \int_{-\infty}^{\frac{z_A-\mu_0}{\sqrt{\frac{d_1^2}{d_1+\delta}}}} \left[\Phi\left(\frac{q_1-\left(1-\gamma+r\left(1-G(t)\right)e_A\right)\left(\sqrt{\frac{d_1^2}{d_1+\delta}}\lambda+\mu_1\right)}{\sigma_2}\right)\right]\varphi(\lambda)d\lambda$$

$$+ (K_A-h-w_A-c)\Phi\left(\frac{z_A-\mu_1}{\sqrt{\frac{d_1^2}{d_1+\delta}}}\right) + c\,. \qquad (A5.2)$$

Next, by differentiating (A5.2) with respect to q_0 we get the second-order derivative

$$\frac{d^2E[SW_1^{AA}(q_1|\mu_1,q_1)}{dq_1^2} = -K_A \int_{-\infty}^{\frac{z_A-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}} \left[\varphi\left(\frac{q_1-(1-\gamma+r\left(1-G(t)\right)e_A)(\sqrt{d_1^2/(d_1+\delta)}\lambda+\mu_1)}{\sigma_2}\right)\varphi(\lambda)\right]/\sigma_2 d\lambda,$$

which is always negative as $\varphi(\cdot) > 0$. Thus, we can infer that $E[SW_1^{AA}(q_1|\mu_1,q_1)]$ is a strictly concave function of q_1.

(ii) We let $X(q_1)^{AA} = -K_A \int_{-\infty}^{\frac{z_A-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}} \left[\Phi\left(\frac{q_1-(1-\gamma+r\left(1-G(t)\right)e_A)(\sqrt{d_1^2/(d_1+\delta)}\lambda+\mu_1)}{\sigma_2}\right)\right]\varphi(\lambda)d\lambda + (K_A - h - w_A - c)\Phi\left(\frac{z_A-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}\right) + c$. The optimal order quantity q_1^{AA*} can be found by solving the first-order condition of Equation (A5.2). From (A5.2), we can see that if $(K_A - h - w_A - c)\Phi\left(\frac{z_A-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}\right) + c \le 0 => r \le \frac{\gamma+w_A+c-\frac{1}{2}-c/\Phi\left(\frac{z_A-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}\right)}{(1-G(t))e_A}$, then $X(q_1)^{AA} < 0$ which means that the optimal order quantity $q_1^{AA*} = 0$ (as q_1^{AA*} cannot be negative); if $r > \frac{\gamma+w_A+c-\frac{1}{2}-c/\Phi\left(\frac{z_A-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}\right)}{(1-G(t))e_A}$, the unique optimal order quantity q_1^{AA*} exists and equals $\max\{0, \arg_{q_1}\{X(q_1)^{AA} = 0\}\}$. (Q.E.D.)

Proof of Proposition 5.2. (i) In Case AB, we use the same approach as the one in Case AA (see Proof of Proposition 5.1) to derive the optimal order quantity in Stage 2:

$$q_2^{AB*} = \max\{0, \mu_2[1-\gamma+r(1-G(t))e_n] + \sigma_2\Phi^{-1}(s) - q_1\}, \quad \text{(A5.3)}$$

where $n = \begin{cases} A, & if\ e_A > e_B \\ B, & if\ e_A \le e_B \end{cases}$ and $s = \begin{cases} \frac{1-2(\gamma+w_B+c-r(1-G(t))e_B)}{1+2(h-\gamma+r(1-G(t))e_B)}, & if\ e_A > e_B \\ \frac{1-2(\gamma+w_B+c-r(1-G(t))e_B)}{1+2(h-\gamma+r(1-G(t))e_A)}, & if\ e_A \le e_B \end{cases}$. From (A5.3) we can observe that $q_2^{AB*} > 0$ when $\mu_2 > \frac{q_0-\sigma_2\Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_n}$ and $q_2^{AB*} = 0$ when $\mu_2 \le \frac{q_0-\sigma_2\Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_n}$.

(ii) If $e_A > e_B$, we have the numerator of $\bar{\mu}^{AB}$, which is independent of e_A and decreasing in e_B as $\frac{ds}{de_B} = \frac{4(1-G(t))r(h+w_B+c)}{(1+2h-2\gamma+2(1-G(t))re_B)^2} > 0$; the denominator of $\bar{\mu}^{UB}$ is increasing in e_A and independent of e_B. Thus, $\bar{\mu}^{AB}$ is decreasing in e_A and e_B. While if $e_A \le e_B$, we have $\frac{ds}{de_A} = -\frac{2(1-G(t))r(1-2\gamma+2(1-G(t))re_B-2(w_B+c))}{(1+2h-2\gamma+2(1-G(t))re_A)^2} < 0$ and $\frac{ds}{de_B} = \frac{2(1-G(t))r}{1+2(h-\gamma+r(1-G(t))e_A)} > 0$, hence the numerator of $\bar{\mu}^{AB}$ is increasing in e_A and decreasing in e_B; the denominator of $\bar{\mu}^{AB}$ is independent of e_A and increasing in e_B. Thus, $\bar{\mu}^{AB}$ is increasing in e_A and decreasing in e_B. (Q.E.D.)

Proof of Lemma 5.2. (i) Recall that we have $K_A = \frac{1}{2} - \gamma - r[1-(1-G(t))e_A] + h + r$, $m_A = \mu_2(1-\gamma+r(1-G(t))e_A)$, $K_B = \frac{1}{2} - \gamma - r[1-(1-G(t))e_B] + h + r$, and $m_B = \mu_2(1-\gamma+r(1-G(t))e_B)$. Similar to Case AA, we obtain the closed-form expression for $E[SW_2^{AB}(q_2^{AB*} = 0|\mu_2, q_1)]$ and $E[SW_2^{AB}(q_2^{AB*} > 0|\mu_2, q_1)]$. For a notational purpose, we define $\tau_A = m_A + \sigma_2\Phi^{-1}(s)$ and $\tau_B = m_B + \sigma_2\Phi^{-1}(s)$.

No matter whether $e_A > e_B$ or $e_A \le e_B$, we have:

$$\begin{aligned} E[SW_2^{AB}(q_2^{AB*} = 0|\mu_2, q_1)] &= E[SW_2^{AA}(q_2^{AA*} = 0|\mu_2, q_1)] \\ &= K_A\left[m_A - \sigma_2\psi\left(\frac{q_1 - m_A}{\sigma_2}\right)\right] - rm_A - hq_1. \end{aligned}$$

When $e_A > e_B$,

$$E[SW_2^{AB}(q_2^{AB*} > 0|\mu_2, q_1)]$$

$$= \left[\frac{1}{2} - \gamma - r\big(1 - \big(1 - G(t)\big)e_A\big)\right] m_A$$

$$- \int_{q_1}^{\infty} \big[v - \gamma - r\big(1 - \big(1 - G(t)\big)e_A\big)\big](x_2 - q_1)\, f(x_2)dx_2$$

$$+ \left[\frac{1}{2} - \gamma - r\big(1 - \big(1 - G(t)\big)e_B\big)\right](m_A - q_1)$$

$$- \int_{\tau_A}^{\infty} \big[v - \gamma - r\big(1 - \big(1 - G(t)\big)e_B\big)\big](x_2 - \tau_A) f(x_2)dx_2 - \int_{\tau_A}^{\infty} r(x_2 - \tau_A)\, f(x_2)dx_2$$

$$- (w_B + c)(\tau_A - q_1) - \int_0^{\infty} h(\tau_A - x_2) f(x_2)dx_2 - \int_{\tau_A}^{\infty} h(x_2 - \tau_A) f(x_2)dx_2\,.$$

$$= \left[\frac{1}{2} - \gamma - r\big(1 - \big(1 - G(t)\big)e_A\big)\right]\left[m_A - \sigma_2\psi\left(\frac{q_1 - m_A}{\sigma_2}\right)\right]$$

$$+ \left[\frac{1}{2} - \gamma - r\big(1 - \big(1 - G(t)\big)e_B\big)\right]\big[m_A - q_1 - \sigma_2\psi\big(\Phi^{-1}(s)\big)\big] - r\sigma_2\psi\big(\Phi^{-1}(s)\big)$$

$$- (w_B + c)(m_A + \sigma_2\Phi^{-1}(s) - q_1) - h\sigma_2\Phi^{-1}(s) - h\sigma_2\psi\big(\Phi^{-1}(s)\big)$$

$$= (K_A - h - r)\left[m_A - \sigma_2\psi\left(\frac{q_1 - m_A}{\sigma_2}\right)\right] + (K_B - h - r - w_B - c)(m_A - q_1)$$

$$- K_B\sigma_2\psi\big(\Phi^{-1}(s)\big) - (h + w_B + c)\sigma_2\Phi^{-1}(s).$$

When $e_A \le e_B$,

$$E[SW_2^{AB}(q_2^{AB*} > 0|\mu_2, q_1)] =$$

$$= \left[\frac{1}{2} - \gamma - r\big(1 - \big(1 - G(t)\big)e_A\big)\right][q_1 - \sigma_2\Phi^{-1}(s) - \int_{\tau_B}^{\infty} (x_2 - \tau_B)\, f(x_2)dx_2]$$

$$+ \left[\frac{1}{2} - \gamma - r\big(1 - \big(1 - G(t)\big)e_B\big)\right][m_B$$

$$- \int_{\tau_B}^{\infty} \big(x_2 - (\tau_B - q_1)\big)\, f(x_2)dx_2](m_A - q_1)] - \int_{\tau_B}^{\infty} r(x_2 - \tau_B) f(x_2)dx_2 - (w_B$$

$$+ c)(\tau_B - q_1) - \int_0^{\infty} h(\tau_B - x_2) f(x_2)dx_2 - \int_{\tau_B}^{\infty} h(x_2 - \tau_B) f(x_2)dx_2$$

$$= \left[\frac{1}{2} - \gamma - r\big(1 - \big(1 - G(t)\big)e_A\big)\right][q_1 - \sigma_2 \Phi^{-1}(s)] + \left[\frac{1}{2} - \gamma - r\big(1 - \big(1 - G(t)\big)e_B\big)\right] m_B$$

$$- (h + w_B)\tau_B + (w_B + c)q_1 + hm_B$$

$$- \left[\frac{1}{2} - \gamma - r\big(1 - \big(1 - G(t)\big)e_A\big)\right] \sigma_2 \psi\big(\Phi^{-1}(s)\big)$$

$$- \left[\frac{1}{2} - \gamma - r\big(1 - \big(1 - G(t)\big)e_B\big)\right] \sigma_1 \psi\left(\frac{\sigma_2 \Phi^{-1}(s) - q_1}{\sigma_2}\right) - (h + r)\sigma_2 \psi\big(\Phi^{-1}(s)\big)$$

$$= (K_A - h - r)\big[q_1 - \sigma_2 \Phi^{-1}(s) - \sigma_2 \psi\big(\Phi^{-1}(s)\big)\big]$$

$$+ (K_B - h - r)\left[m_B - \sigma_2 \psi\left(\frac{\sigma_2 \Phi^{-1}(s) - q_1}{\sigma_2}\right)\right] - (h + r)\sigma_2 \psi\big(\Phi^{-1}(s)\big)$$

$$- (h + w_B + c)\sigma_2 \Phi^{-1}(s) - (m_B - q_1)(w_B + c).$$

Then, by using the same method as the one used in Case AA (see Proof of Lemma 5.1), we obtain the first-order and the second- order conditions in Case AB as follows.

When $e_A > e_B$, we let

$$X(q_1)^{AB} = \frac{dE[SW_1^{AB}(q_1|\mu_1, q_1)}{dq_1}$$

$$= -(K_A - h - r)\Phi(\frac{q_1 - m_A}{\sigma_2}) - (h$$

$$+ r)\int_{-\infty}^{\frac{z_A - \mu_1}{\sqrt{d_1^2/(d_1+\delta)}}} \left[\Phi\left(\frac{q_1 - (1 - \gamma + r\big(1 - G(t)\big)e_A)(\sqrt{d_1^2/(d_1 + \delta)}\lambda + \mu_1)}{\sigma_2}\right)\right]\varphi(\lambda)d\lambda$$

$$+ (K_B - h - w_B - c)\Phi\left(\frac{z_A - \mu_1}{\sqrt{d_1^2/(d_1 + \delta)}}\right) + K_A - K_B + w_B + c - w_A,$$

$$\frac{d^2E[SW_1^{AB}(q_1|\mu_1, q_1)}{dq_1^2}$$

$$= (K_A - h - r)[1 - \varphi(\frac{q_1 - m_A}{\sigma_2})] - (h$$

$$+ r)\int_{-\infty}^{\frac{z_A - \mu_1}{\sqrt{d_1^2/(d_1+\delta)}}} \left[\varphi\left(\frac{q_1 - (1 - \gamma + r\big(1 - G(t)\big)e_A)(\sqrt{d_1^2/(d_1 + \delta)}\lambda + \mu_1)}{\sigma_2}\right)\varphi(\lambda)\right]$$

$$/\sigma_2 d\lambda.$$

Thus, we derive the strict concavity condition of $E[SW_0^{AB}(q_0|\mu_0, q_0)]$ by letting $\frac{d^2E[SW_1^{AB}(q_1|\mu_1, q_1)}{dq_1^2} < 0 => h > \bar{h}$, where

$$\bar{h} = \frac{(K_A - h + g - r)[1 - \varphi(\frac{q_1 - m_A}{\sigma_2})]}{\int_{-\infty}^{\frac{z_A - \mu_1}{\sqrt{d_1^2/(d_1+\delta)}}} \left[\varphi\left(\frac{q_1 - (1-\gamma+r(1-G(t))e_A)(\sqrt{d_1^2/(d_1+\delta)}\lambda + \mu_1)}{\sigma_2}\right)\varphi(\lambda)\right]/\sigma_2 d\lambda.} - r.$$

When $e_A \leq e_B$,

$$X(q_1)^{AB} = \frac{dE[SW_1^{AB}(q_1|\mu_1, q_1)}{dq_1}$$

$$= -K_A \int_{-\infty}^{\frac{z_B - \mu_1}{\sqrt{d_1^2/(d_1+\delta)}}} \left[\Phi\left(\frac{q_1 - (1-\gamma+r(1-G(t))e_B)(\sqrt{d_1^2/(d_1+\delta)}\lambda + \mu_1)}{\sigma_2}\right)\right]\varphi(\lambda)d\lambda$$

$$+ (K_B - h - r)\{\sigma_2\psi\left(\frac{q_1 - \sigma_2\Phi^{-1}(s)}{\sigma_2}\right) - \int_{-\infty}^{\frac{z_B - \mu_1}{\sqrt{d_1^2/(d_1+\delta)}}}\left[\Phi(\frac{q_1 - \sigma_2\Phi^{-1}(s)}{\sigma_2})\right]\varphi(\lambda)d\lambda\} + K_A$$

$$+ K_B - w_B - c - w_A - 2(h + r),$$

$$\frac{d^2E[SW_1^{AB}(q_1|\mu_1, q_1)}{dq_1^2}$$

$$= -K_A \int_{-\infty}^{\frac{z_B - \mu_1}{\sqrt{d_1^2/(d_1+\delta)}}} \left[\varphi\left(\frac{q_1 - (1-\gamma+r(1-G(t))e_B)(\sqrt{d_1^2/(d_1+\delta)}\lambda + \mu_1)}{\sigma_2}\right)\varphi(\lambda)\right]$$

$$/\sigma_2 d\lambda + (K_B - h - r)\{1 + \varphi(\frac{q_1 - \sigma_2\Phi^{-1}(s)}{\sigma_2})$$

$$- \int_{-\infty}^{\frac{z_B - \mu_1}{\sqrt{d_1^2/(d_1+\delta)}}}\left[\Phi\left(\frac{q_1 - \sigma_2\Phi^{-1}(s)}{\sigma_2}\right)\varphi(\lambda)\right]/\sigma_2 d\lambda\}.$$

We then derive the strict concavity condition of $E[SW_1^{AB}(q_1|\mu_1, q_1)]$ by letting $\frac{d^2E[SW_1^{AB}(q_1|\mu_1, q_1)}{dq_1^2} < 0 => h > \bar{h}$, where

$$\bar{h} = K_B - r - \frac{K_A \int_{-\infty}^{\frac{z_B - \mu_1}{\sqrt{d_1^2/(d_1+\delta)}}} \left[\varphi\left(\frac{q_1 - (1-\gamma+r(1-G(t))e_B)(\sqrt{d_1^2/(d_1+\delta)}\lambda + \mu_1)}{\sigma_2}\right)\varphi(\lambda)\right]/\sigma_2 d\lambda}{1 + \varphi(\frac{q_1 - \sigma_2\Phi^{-1}(s)}{\sigma_2}) - \int_{-\infty}^{\frac{z_B - \mu_1}{\sqrt{d_1^2/(d_1+\delta)}}}\left[\Phi\left(\frac{q_1 - \sigma_2\Phi^{-1}(s)}{\sigma_2}\right)\varphi(\lambda)\right]/\sigma_2 d\lambda}.$$

(ii) Similar to Proof of Lemma 5.1(ii), the threshold of r can be derived by observing $X(q_1)^{AB}$.

(Q.E.D.)

Proof of Proposition 5.3. Recall that we have $q_2^{AA*} = \max\Big\{0, \mu_2[1 - \gamma + r(1 - G(t))e_A] + \sigma_2\Phi^{-1}\left(\frac{1-2(\gamma+w_A+c-r(1-G(t))e_A)}{1+2(h-\gamma+r(1-G(t))e_A)}\right) - q_1\Big\}$, and $q_2^{AB*} = \max\{0, \mu_2[1 - \gamma + r(1 - G(t))e_n] +$

$\sigma_2\Phi^{-1}(s) - q_1\}$, where $n = \begin{cases} A, & if\ e_A > e_B \\ B, & if\ e_A \le e_B \end{cases}$ and $s = \begin{cases} \frac{1-2(\gamma+w_B+c-r(1-G(t))e_B)}{1+2(h-\gamma+r(1-G(t))e_B)}, & if\ e_A > e_B \\ \frac{1-2(\gamma+w_B+c-r(1-G(t))e_B)}{1+2(h-\gamma+r(1-G(t))e_A)}, & if\ e_A \le e_B \end{cases}$.

For given q_1, if $e_A > e_B$, then $q_2^{AA*} - q_2^{AB*} = \mu_2\left[1-\gamma+r\left(1-G(t)\right)e_A\right] + \sigma_2\Phi^{-1}\left(\frac{1-2\left(\gamma+w_A+c-r\left(1-G(t)\right)e_A\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_A\right)}\right) - q_1 - \mu_2\left[1-\gamma+r\left(1-G(t)\right)e_A\right] - \sigma_2\Phi^{-1}\left(\frac{1-2\left(\gamma+w_B+c-r\left(1-G(t)\right)e_B\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_B\right)}\right) + q_1 = \sigma_2[\Phi^{-1}\left(\frac{1-2\left(\gamma+w_A+c-r\left(1-G(t)\right)e_A\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_A\right)}\right) - \Phi^{-1}\left(\frac{1-2\left(\gamma+w_{B+c}-r\left(1-G(t)\right)e_B\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_B\right)}\right)]$; hence, $q_2^{AA*} < q_2^{AB*}$ if and only if $\Phi^{-1}\left(\frac{1-2\left(\gamma+w_A+c-r\left(1-G(t)\right)e_A\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_A\right)}\right) - \Phi^{-1}\left(\frac{1-2\left(\gamma+w_B+c-r\left(1-G(t)\right)e_B\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_B\right)}\right) < 0 \Rightarrow w_A < \arg_{w_A}\{\Phi^{-1}\left(\frac{1-2\left(\gamma+w_A+c-r\left(1-G(t)\right)e_A\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_A\right)}\right) = \Phi^{-1}\left(\frac{1-2\left(\gamma+w_B+c-r\left(1-G(t)\right)e_B\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_B\right)}\right)\}$.

If $e_A \le e_B$, then $q_2^{AA*} - q_2^{AB*} = \mu_2\left[1-\gamma+r\left(1-G(t)\right)e_A\right] + \sigma_2\Phi^{-1}\left(\frac{1-2\left(\gamma+w_A+c-r\left(1-G(t)\right)e_A\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_A\right)}\right) - q_1 - \mu_2\left[1-\gamma+r\left(1-G(t)\right)e_B\right] - \sigma_2\Phi^{-1}\left(\frac{1-2\left(\gamma+w_B+c-r\left(1-G(t)\right)e_B\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_A\right)}\right) + q_1 = \mu_2\left[r\left(1-G(t)\right)(e_A - e_B)\right] + \sigma_2[\Phi^{-1}\left(\frac{1-2\left(\gamma+w_A+c-r\left(1-G(t)\right)e_A\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_A\right)}\right) - \Phi^{-1}\left(\frac{1-2\left(\gamma+w_B+c-r\left(1-G(t)\right)e_B\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_A\right)}\right)]$; hence, $q_2^{AA*} < q_2^{AB*}$ if and only if $\mu_2\left[r\left(1-G(t)\right)(e_A - e_B)\right] + \sigma_2[\Phi^{-1}\left(\frac{1-2\left(\gamma+w_A+c-r\left(1-G(t)\right)e_A\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_A\right)}\right) - \Phi^{-1}\left(\frac{1-2\left(\gamma+w_B+c-r\left(1-G(t)\right)e_B\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_A\right)}\right)] < 0 \Rightarrow \mu_2 > \frac{\sigma_2[\Phi^{-1}\left(\frac{1-2\left(\gamma+w_A+c-r\left(1-G(t)\right)e_A\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_A\right)}\right) - \Phi^{-1}\left(\frac{1-2\left(\gamma+w_B+c-r\left(1-G(t)\right)e_B\right)}{1+2\left(h-\gamma+r\left(1-G(t)\right)e_A\right)}\right)]}{r\left(1-G(t)\right)(e_B - e_A)}$. (Q.E.D.)

Proof of Proposition 5.4. First, the objective functions in the blockchain adoption case can be checked as below.

Case AA:

$$C_2^{BT,AA} = E[(w_A + b + c)q_2 + h(q_1 + q_2 - D_2)^+],$$

$$CS_2^{BT,AA} = E\left[\left(v - \gamma - r(1-e_A)\right)\min(D_2, q_1 + q_2) + (-r)((q_1 + q_2 - D_2)^-)\right],$$

$$SW_2^{BT,AA}(q_2|\mu_2, q_1) = CS_2^{BT,AA} - C_2^{BT,AA}.$$

Case AB:

$$C_2^{BT,AB} = E[(w_B + b + c)q_2 + h(q_1 + q_2 - D_2)^+],$$

$$CS_2^{BT,AB} = \begin{cases} E[\big(v-\gamma-r(1-e_A)\big)\min(D_2,q_1) + \\ \big(v-\gamma-r(1-e_B)\big)\min((D_2-q_1)^+,q_2) + (-r)((q_1+q_2-D_2)^-)] & ,if\ e_A > e_B \\ E[\big(v-\gamma-r(1-e_A)\big)\min((D_2-q_2)^+,q_1) + \\ \big(v-\gamma-r(1-e_B)\big)\min(D_2,q_2) + (-r)((q_1+q_2-D_2)^-)] & ,if\ e_A \le e_B \end{cases},$$

$$SW_2^{BT,AB}(q_2|\mu_2,q_1) = CS_2^{BT,AB} - C_2^{BT,AB}.$$

For Case AA, we derive $q_2^{BT,AA*} = \max\{0,\mu_2(1-\gamma+re_A)+\sigma_2\Phi^{-1}(s^{BT})-q_1\}$, where $s^{BT} = \frac{1-2(\gamma+w_A+b-re_A)}{1+2(h-\gamma+re_A)}$.

For Case AB, we derive $q_2^{BT,AB*} = \max\{0,\mu_2(1-\gamma+re_n)+\sigma_2\Phi^{-1}(s^{BT})-q_1\}$, where $n = \begin{cases} A & ,if\ e_A > e_B \\ B & ,if\ e_A \le e_B \end{cases}$, $s^{BT} = \begin{cases} \frac{1-2(\gamma+w_B+b-re_B)}{1+2(h-\gamma+re_B)} & ,if\ e_A > e_B \\ \frac{1-2(\gamma+w_B+b-re_B)}{1+2(h-\gamma+re_A)} & ,if\ e_A \le e_B \end{cases}$, and s^{BT} represents the inventory service level of the vaccine in Stage 2 with blockchain adoption. Before we proceed to show the proof of Proposition 5.4, we derive Lemma A1 as follows.

Lemma A1. *(i) When* $\mu_2 > \bar{\mu}^{BT,i}$*, we have* $q_2^{BT,i*} > 0$*; when* $\mu_2 \le \bar{\mu}^{BT,i}$*, we have* $q_2^{BT,i*} = 0$*, where* $\bar{\mu}^{BT,i} = \begin{cases} \frac{q_1-\sigma_2\Phi^{-1}(s^{BT})}{1-\gamma+re_A}, & if\ i = AA \\ \frac{q_1-\sigma_2\Phi^{-1}(s^{BT})}{1-\gamma+re_n}, & if\ i = AB \end{cases}$*. (ii)* $\bar{\mu}^{BT,i}$ *is increasing in* b*.*

Lemma A1 examines the optimal order quantity in Stage 1, which uncovers similar findings to the ones in the basic model where the blockchain technology is absent. The key finding is that only when the updated market size (i.e., μ_2) is relatively large, will the government order the vaccine in Stage 2. Besides, we notice that a high unit cost of blockchain adoption will reduce the government's willingness to order in Stage 2 because the high cost will lead to a low inventory service level.

Proof of Lemma A1. (i) By adopting the same method as the one in the basic model (see Proofs of Propositions 5.1 and 5.2), we can get the results. (ii) We have $\frac{ds^{BT}}{db} = \begin{cases} \frac{-2}{1+2(h-\gamma+re_B)} < 0, & if\ e_A > e_B \\ \frac{-2}{1+2(h-\gamma+re_A)} < 0, & if\ e_A \le e_B \end{cases}$, which means that the numerator of $\bar{\mu}^{BT,i}$ is always increasing in b, and the denominator of $\bar{\mu}^{BT,i}$ is independent of b; thus, $\bar{\mu}^{BT,i}$ is always increasing in b.

Then, we yield the expected benefit-to-go in Stage 1 as follows. We let $K_A^{BT} = \frac{1}{2} - \gamma - r(1-e_A) + h + r$, $m_A^{BT} = \mu_2(1-\gamma+re_A)$, $K_B^{BT} = \frac{1}{2} - \gamma - r(1-e_B) + h + r$, and $m_B = \mu_2(1-\gamma+$

re_B), and we have:

$$SW_1^{BT,i}(q_1|\mu_1) = \int_{-\infty}^{\frac{q_1-\sigma_2\Phi^{-1}(s^{BT})}{1-\gamma+re_A}} E\left[SW_2^{BT,i}\left(q_2^{BT,i*}=0\middle|\mu_2,q_1\right)\right] f(\mu_2)d\mu_2 + \int_{\frac{q_1-\sigma_2\Phi^{-1}(s^{BT})}{1-\gamma+re_A}}^{\infty} E\left[SW_2^{BT,i}\left(q_2^{BT,i*}>0\middle|\mu_2,q_1\right)\right] f(\mu_2)d\mu_2 - (w_A+b)q_1 - F,$$

where $n = \begin{cases} A & ,if\ i = AA\ or\ (i = AB\ and\ e_A > e_B) \\ B & ,if\ i = AB\ and\ e_A \le e_B \end{cases}$, and

$$E\left[SW_2^{BT,AA}\left(q_2^{BT,AA*}=0\middle|\mu_2,q_1\right)\right] = E\left[SW_2^{BT,AB}\left(q_2^{BT,AB*}=0\middle|\mu_2,q_1\right)\right] = K_A^{BT}\left[m_A^{BT} - \sigma_2\Psi\left(\frac{q_1-m_A^{BT}}{\sigma_2}\right)\right] - rm_A^{BT} - hq_1, \text{ and}$$

$$E\left[SW_2^{BT,AB}\left(q_2^{BT,AB*}>0\middle|\mu_2,q_1\right)\right] =$$

$$\begin{cases} (K_A^{BT}-h-r)\left[m_A^{BT}-\sigma_2\psi\left(\frac{q_1-m_A^{BT}}{\sigma_2}\right)\right] + (K_B^{BT}-h-r-w_B-c-b)(m_A^{BT}-q_1) - \\ K_B^{BT}\sigma_2\psi\left(\Phi^{-1}(s^{BT})\right) - (h+w_B+c+b)\sigma_2\Phi^{-1}(s^{BT}) & ,if\ e_A > e_B \\ (K_A^{BT}-h-r)\left[q_1-\sigma_2\Phi^{-1}(s^{BT})-\sigma_2\psi\left(\Phi^{-1}(s^{BT})\right)\right] + (K_B^{BT}-h-r) \\ \left[m_B^{BT}-\sigma_2\psi\left(\frac{\sigma_2\Phi^{-1}(s^{BT})-q_1}{\sigma_2}\right)\right] - (h+r)\sigma_2\psi\left(\Phi^{-1}(s^{BT})\right) - \\ (h+w_B+c+b)\sigma_2\Phi^{-1}(s^{BT}) - (m_B^{BT}-q_1)(w_B+c+b) & ,if\ e_A \le e_B \end{cases}$$

.

Based on the above expected benefit-to-go functions in Stage 1, we derive the optimal order quantity q_1 for the government as $q_1^{BT,AA*} = \max\{0, \arg_{q_1}\{X(q_1)^{BT,AA}=0\}\}$ and $q_1^{BT,AB*} = \max\{0, \arg_{q_1}\{X(q_1)^{BT,AB}=0\}\}$, where $z_A^{BT} = \frac{q_1-\sigma_2\Phi^{-1}(s^{BT})}{1-\gamma+re_A}$, $\lambda = \frac{\mu_2-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}$, $X(q_1)^{BT,AA} = -K_A^{BT}\int_{-\infty}^{\frac{z_A^{BT}-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}}\left[\Phi\left(\frac{q_1-(1-\gamma+re_A)(\sqrt{d_1^2/(d_1+\delta)}\lambda+\mu_1)}{\sigma_2}\right)\right]\varphi(\lambda)d\lambda + (K_A^{BT}-h-w_A-c-b)\Phi\left(\frac{z_A^{BT}-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}\right)+c$, $X(q_1)^{BT,AB} = \frac{dE[SW_1^{BT,AB}(q_1|\mu_1,q_1)}{dq_1} = -(K_A^{BT}-h-r)\Phi(\frac{q_1-m_A}{\sigma_2}) - (h+r)\int_{-\infty}^{\frac{z_A-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}}\left[\Phi\left(\frac{q_1-(1-\gamma+re_A)(\sqrt{d_1^2/(d_1+\delta)}\lambda+\mu_1)}{\sigma_2}\right)\right]\varphi(\lambda)d\lambda + (K_B^{BT}-h-w_B-b)\Phi\left(\frac{z_A-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}\right) + K_A^{BT} - K_B^{BT} + w_B + b - w_A$ when $e_A > e_B$, and $X(q_1)^{BT,AB} = \frac{dE[SW_1^{BT,AB}(q_1|\mu_1,q_1)}{dq_1} = -K_A^{BT}\int_{-\infty}^{\frac{z_B-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}}\left[\Phi\left(\frac{q_1-(1-\gamma+re_B)(\sqrt{d_1^2/(d_1+\delta)}\lambda+\mu_1)}{\sigma_2}\right)\right]\varphi(\lambda)d\lambda + (K_B^{BT}-h-$

$r)\{\sigma_2\psi\left(\frac{q_1-\sigma_2\Phi^{-1}(s^{BT})}{\sigma_2}\right)-\int_{-\infty}^{\frac{z_B-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}}\left[\Phi(\frac{q_1-\sigma_2\Phi^{-1}(s^{BT})}{\sigma_2})\right]\varphi(\lambda)d\lambda\}+K_A^{BT}+K_B^{BT}-w_B-b-w_A-2(h+r)$ when $e_A\le e_B$ (P.S.: by using the same methods as the ones in Proof of Lemma 5.2).

Then, (i) in Case AA, $\frac{s^{BT}}{s}=\frac{[1-2(\gamma+w_A+b-r)][1+2(h-\gamma+r(1-G(t))e_A)]}{[1-2(\gamma+w_A-r(1-G(t))e_A)][1+2(h-\gamma+re_A)]}$ where $1-2(\gamma+w_A+b-r)<1-2(\gamma+w_A-r(1-G(t))e_A)$ and $1+2(h-\gamma+r(1-G(t))e_A)<1+2(h-\gamma+re_A)$ (as $0<1-G(t)<1$); thus, we have $s^{BT}<s\Rightarrow z_A^{BT}>z_A\Rightarrow X(q_1)^{BT,AA}<X(q_1)^{AA}$. Moreover, since we know that $X(q_1)^{AA}$ is decreasing in q_1 (i.e., $\frac{d^2E[SW_1^{AB}(q_1|\mu_1,q_1)}{dq_1^2}<0$), we can infer that $q_1^{BT,AA*}>q_1^{AA*}$. (ii) For given q_1, $q_2^{BT,AA*}-q_2^{AA*}=\mu_2(1-\gamma+re_A)+\sigma_2\Phi^{-1}(s^{BT})-\mu_2[1-\gamma+r(1-G(t))e_A]-\sigma_2\Phi^{-1}(s)=\mu_2re_AG(t)+\sigma_2[\Phi^{-1}(s^{BT})-\Phi^{-1}(s)]$, where $s^{BT}=\frac{1-2(\gamma+w_A+b-re_A)}{1+2(h-\gamma+re_A)}$ and $s=\frac{1-2(\gamma+w_A-r(1-G(t))e_A)}{1+2(h-\gamma+r(1-G(t))e_A)}$. Hence, $q_2^{BT,AA*}>q_2^{AA*}$ if and only if $\mu_2re_AG(t)+\sigma_2[\Phi^{-1}(s^{BT})-\Phi^{-1}(s)]>0\Rightarrow G(t)>\frac{\sigma_2[\Phi^{-1}(s)-\Phi^{-1}(s^{BT})]}{\mu_2re_A}$. (Q.E.D.)

Proof of Proposition 5.5. The method used in Proposition 5.5 is the same with the one in the basic, i.e., see Proofs of Propositions 5.1 and 5.2. For s^{SE}, since $\frac{\partial s^{SE}}{\partial L_n}=\frac{-4(h+w_A)}{(1+2h-2\gamma+2(1-G)re_n-2L_n)^2}<0$ (where $n=A$ or B), we have $s^{SE}<s$. For $\bar{\mu}^{SE,i}$, since $\bar{\mu}^{SE,i}$ is decreasing in s^{SE} and $s^{SE}<s$, we get $\bar{\mu}^{SE,i}>\bar{\mu}^i$. (Q.E.D.)

Proof of Findings in Figure 5-3. First, recall that we have $\tilde{r}=\frac{\gamma+w_A+c-\frac{1}{2}-c/\Phi\left(\frac{z_A-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}\right)}{(1-G(t))e_A}$. Since $\frac{d\tilde{r}}{dt}=\frac{\gamma+w_A+c-\frac{1}{2}-c/\Phi\left(\frac{z_A-\mu_1}{\sqrt{d_1^2/(d_1+\delta)}}\right)}{(1-G(t))^2e_A}>0$ and we know that $G(t)$ is increasing in t, we can derive that $\tilde{r}$ is increasing in t. For the impact of t on $\dot{r}$ and $\ddot{r}$, please refer to Figure A5-15 in Appendix A for details. (Q.E.D.)

Appendix C —— Interview Guide and Original Data

I. Interview of Chapter 3

Objectives:

1. Changes that COVID-19 brings to salespersons, consumers and physical stores.
2. Changes that WhatsApp shopping brings to salespersons, consumers and physical stores.
3. When to implement WhatsApp shopping?
4. Where the salespersons to provide service to WhatsApp consumers?

Open-ended questions:

a. (To validate 1) The impacts of COVID-19 on physical stores and employees?

- Physical stores
- Operation modes (WSO)

b. (To validate 2, 3 and 4) How to sell products on WhatsApp？

- When (before or after COVID-19 pandemic)
- Where (in stores or other places)
- What (what service can be provided): take some photos in physical stores, make recommendations.
- How to pay & any Delivery cost?
- Employee’s salary

c. (To validate 1 and 2) Do you feel any changes of consumers?

- Shift from physical store to WhatsApp.
- They are afraid to shop in the store
- They prefer to shop online but care about shipment issues.

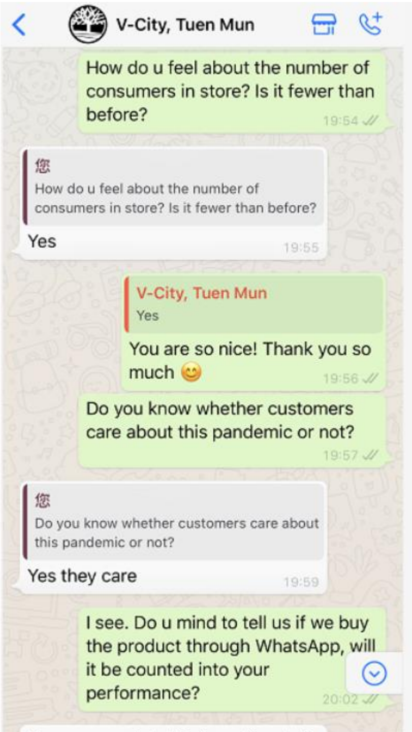
Descriptions of interview:

We focus on the WSO case of Timberland Hong Kong and try to interview salespersons who are responsible for their stores’ WhatsApp accounts with and without indicating that our research intention. In order to achieve interview objectives which are described in the Interview Guide, we interview two salespersons who work in the Tuen Mun Plaza store and the V City Tuen Mun store. Noticeably, we indicated our purpose for chatting with him/her as a research interview when we interviewed the salesperson of V City Tuen Mun; while we pretended to order products through WhatsApp when we interviewed the salesperson of Tuen Mun Plaza Store. According to our interview with these two salespersons, we summarize the interview results in Table 3-1 in the main body.

<u>Original data of the interview:</u>

Table C1. Interview results.

Data of interview with the salesperson in V City Tuen Mun store



Data of interview with the salesperson in Tuen Mun Plaza store[21]
  

21 Dialog with the salesperson in Timberland Tuen Mum plaza has been translated into English and provided at the end.

<u>Dialog with the salesperson in Timberland Tuen Mum plaza:</u>

…

Salesperson: Hi. Yes, we have this product. What size do you want?

Us: May you please take a photo for me?

Salesperson: (photo)

Us: Let me see…

Salesperson: Sure, no problem.

Us: It's free delivery, right?

Salesperson: Yes. Make the payment by PayMe, and then you can enjoy the free delivery.

Us: Haha so interesting way to buy a product! When did you start to sell through WhatsApp? I haven't tried it before.

Salesperson: Around three months. We want to provide more channels for consumers to make the purchase.

Us: Hahaha is it because of COVID-19?

Salesperson: That is one of the reasons. Besides, due to the popularity of online shopping, we started to provide this kind of service.

Us: BTW, can free delivery for a T-shirt only? I see that yellow one is nice.

Salesperson: (photo) This one?

Us: Yes yes.

Salesperson: Yes. What size do you want? I can help check whether it is in stock.

Us: 168cm/50kg. Which size?

Salesperson: Excuse me, how much your waist is?

Us: Not sure. Maybe the smallest size?

Salesperson: Sorry that we only have the L size.

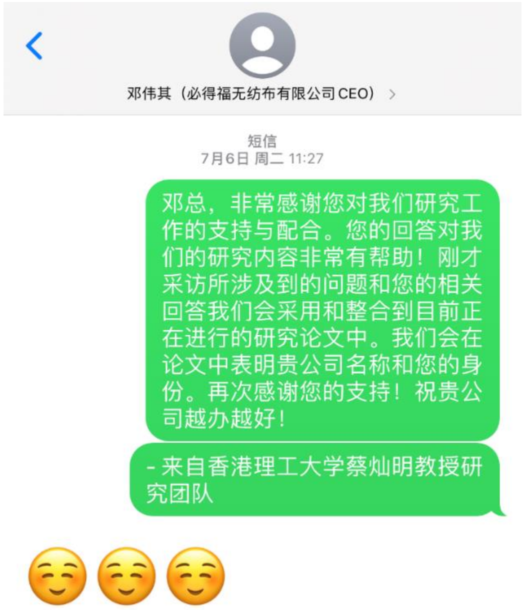
Us: Let me find more about hoodie, T-shirt…

(End)

II. Interview of Chapter 4

<u>Interviewee:</u> Weiqi Deng, CEO of Foshan Nanhai Beautiful Nonwoven Co., Ltd.

Approval from the interviewee:

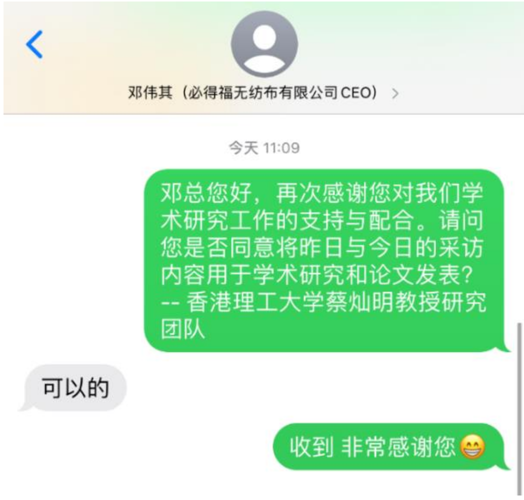


6 July 2021

Interviewer: Dear Deng, thanks much for your kind support and cooperation for our research work. Your answers in the interview are very helpful to our study! *The interview questions and the related answers will be included in our research paper; and we will show the name of your company and your identity in the paper as well*. Thanks again for your support. Wish your company a brilliant prospect.

—— The Hong Kong Polytechnic University, Professor Tsan-Ming Choi's research team.

Interviewee: ^_^



7 July 2021

Interviewer: Dear Deng, thanks again for your kind support and cooperation for our research work. *I am writing to ask whether you agree for us to include the interview results into the publication of research paper?*

—— The Hong Kong Polytechnic University, Professor Tsan-Ming Choi's research team.

Interviewee: *Approve*.

Interviewer: Well-received with many thanks. ^_^

Purpose of interview:

1. To identify the features of mask supply chain (MSC) under COVID-19.
2. To understand the subsidies and policies implemented by the government to MSC.
3. To explore the impacts of government's subsidies and policies on MSC.

Interview question/outline:

d. (To validate 1) When and why your company started to produce masks?

- High demand/profitability?
- Quick production?

Answers: (i) At the beginning of COVID-19, the firm realized the huge market demand in mainland China, Hong Kong, and Japan. (ii) The company had equipment to support the production. The production requires simple equipment and materials for "single-use face and surgical" masks with lower quality, while relatively complex equipment and materials for respirator masks (e.g., N95, N99, etc.) with higher quality.

e. (To validate 1) What are the specific challenges faced by your department in terms of mask production under COVID-19?

- Supply disruption?
- Yield problem?

Answers: Since our firm (i.e., Foshan Nanhai Beautiful Nonwoven Co., Ltd) has its own raw material production line, the firm did not meet the supply disruption risk during the pandemic. However, the cost of material production is higher than before. While if the firm does not have own raw material production line, it is very likely to face high supply disruption risk.

f. (To validate 1) What are the important decisions for mask production?

- Price?
- Quality?

Answers: (i) The firm makes pricing decisions carefully during the COVID-19 pandemic: higher price at the beginning; lower price later. (ii) The firm sets different quality levels for different orders of masks: higher quality for the orders from medical facilities; lower quality for the orders from general market.

g. (To validate 2) Are there any subsidies provided by the government for mask production?

- If yes, when did it start? What are the specific policies? How does the government supervise? Is there any price control policy? Any comments on subsidy schemes (including consumer subsidy scheme and manufacturer subsidy scheme)?
- If no, do you think providing subsidies can help?

Answers: (i) Yes, the government provided the subsidies to the mask supply chain, including subsidizing mask production and warehouse construction. The subsidy amount is reduced with the pandemic period.; and starting from August 2020, there is no subsidy provided. (ii) The government imposed the price control policy during the pandemic.

h. (To validate 3 — If yes for c) Are there any positive/negative impacts of the subsidies/policies on mask production?

- Quality/Quantity side
- Profit side
- Anything else

Answers: The government subsidy program has resulted in an increased production capacity; with the subsidy program, the firm has successfully proposed "Ten Million Mask Plan", which helps the MSC to match the increased demand during the pandemic.

i. (To validate 3 — If no for c) Without the government's support, is it beneficial to compete with the professional mask manufacturers, e.g., 3M?

Answers: N/A