IISE Transactions

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/uiie21

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To cite this article: Xiaoyan Xu, Suresh P. Sethi, Sai-Ho Chung & Tsan-Ming Choi (2023): Ordering COVID-19 Vaccines for Social Welfare with Information Updating: Optimal Dynamic Order Policies and Vaccine Selection in the Digital Age, IISE Transactions, DOI: 10.1080/24725854.2023.2204329

To link to this article: https://doi.org/10.1080/24725854.2023.2204329

Ordering COVID-19 Vaccines for Social Welfare with Information Updating: Optimal Dynamic Order Policies and Vaccine Selection in the Digital Age

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Abstract

In the digital age, operations can be improved by a wise use of information and technological tools. During the COVID-19 pandemic, governments faced various vaccine choices having different efficacy and availability levels at different time points. In this paper, we consider a two-stage vaccine ordering problem of a government 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. Using dynamic programming, we derive the government's optimal vaccine ordering policy. We find 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 order nothing at the first stage and order from the supplier with a higher efficacy level at the second stage. When the disease's infection rate is high, the government should order vaccines at the first stage and switch to the other supplier with a lower efficacy level at the second stage. We extend our model to examine (i) the value of blockchain adoption and (ii) the impact of vaccines' side effects.

Keywords: Vaccine supply chain; two-stage ordering; information updating; social welfare; blockchain; COVID-19.

1 **Introduction**

1.1 *Motivation and Background*

Since 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, 2020). 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 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 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.

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°C, 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).

1.2 *Research Questions and Major Findings*

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 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.

1.3 *Contribution Statements and Paper's Organization*

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.

The remainder of this paper is organized as follows. We conduct the literature review for prior related literature in Section 2. Section 3 establishes the basic model and derives the corresponding optimal solutions. We analyze the impacts of critical factors and find the optimal ordering policy in Section 4. Next, Section 5 extends the analyses to check the (i) ordering policy with blockchain adoption for cold chain distribution and (ii) ordering policy considering the vaccine's side effects. Finally, we conclude our study in Section 6. All supplementary figures for numerical analyses and technical proofs are in Online Appendix.

2 **Literature Review**

Our research is related to three streams in industrial engineering and operations management, namely, (i) vaccine supply chain management, (ii) two-stage ordering with information updating, and (iii) blockchain adoption in supply chain management. We concisely review them as follows.

First, the vaccine supply chain has been getting increased attention in the past years. It consists of four aspects: "product, production, allocation, and distribution" (Duijzer et al., 2018). Some prior studies focus on the optimal vaccine selection problem. For example, Wu et al. (2005) build an analytically tractable model to investigate the annual vaccine-strains selection process under the "follow policy" proposed by WHO. Then, Robbins and Jacobson (2011) examine the government's optimal vaccine selection decisions in the pediatric vaccine market. The government can negotiate prices and quantities with vaccine producers in their model. Robbins and Lunday (2016) pay attention to the consumer choice problem in a vaccine supply chain comprising an upper-level manufacturer and lower-level customers. In their model, consumers are asked to choose the vaccines that can minimize cost while immunizing against one or more diseases.

Regarding vaccine production issues, uncertainty in design, delivery, and demand is the most crucial factor that prior studies focus on (Dai, 2015). To be specific, Chick et al. (2008) highlight the vaccine's insufficient supply problem due to the manufacturer's production risk/uncertainty. Arifoğlu et al. (2012) explore how to improve the influenza vaccine supply chain operations considering the yield uncertainty issue and self-interested consumers. Arifoğlu and Tang (2021) analytically investigate a two-side incentive program implemented to support the flu vaccine supply chain with an uncertain production yield under an ex-ante balanced budget. Lin et al. (2022) consider the uncertainty risks from both supply and demand sides in the vaccine supply chain, where a social planner exists to coordinate the supply chain. The scarcity of vaccines under unexpected outbreaks makes the optimal allocation problem in the vaccine supply chain relatively complex. Sun et al. (2009) and Mamani et al. (2013) examine the value of coordination among different countries in the vaccine allocation process. Their results show that a lack of coordination may lead to vaccine disruption in some regions. Inventory control is a critical issue in both the allocation and distribution process. Salmerón and Apte (2010) propose a two-stage stochastic programming formulation to minimize expected casualties. Yarmand et al. (2014) study the optimal "vaccine allocation problem" by constructing a stochastic optimization decision framework over multiple locations. The authors examine how the development of an epidemic influences quantity decisions in different stages. Similar to Salmerón and Apte (2010) and Yarmand et al. (2014), we construct a two-stage two-ordering inventory model and derive the government's optimal ordering decisions for vaccines under an uncertain demand during the pandemic. Unlike the prior literature, we base our work on the practices observed during the COVID-19 pandemic and integrate crucial characteristics of the vaccine supply chain, such

as vaccines' efficacy, the disease's infection rate, shipping time, cold chain requirement, etc. into the models.

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). Moreover, motivated by the quick response policy and many related topics, many important studies have appeared since the mid-1990s (e.g., Fisher et al. 1994). 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). Huang et al. (2005) evaluate a two-stage purchase contract by which the buyer can adjust its purchasing decision upon updating the demand forecast and provide suggestions on improving the forecast quality and contract design. Chen et al. (2010) work on a coordination contract, focusing mainly on fashionable products with a short selling season and huge demand uncertainty. To coordinate the supply chain, the authors propose a three-parameter contract to share risk and profit in a two-stage setting. Chan et al. (2018) and Zhang et al. (2020) focus on investigating the values of quick response (QR) in the supply chain's inventory problem. Chan et al. (2018) establish a two-echelon channel using green technology. The authors use Bayesian theory to capture the information updating of cleaner technology. Similarly, Zhang et al. (2020) build a two-stage supply chain with Bayesian demand information updating. The authors uncover how flexibility can affect QR by comparing the single-ordering and two-ordering cases. Chao et al. (2021) work on food supply chains and propose a two-stage location–routing–inventory model with time windows and vehicle capacity constraints. Their finding implies that customer sequence will significantly impact the results due to the associated energy cost. Similar to the prior literature, we adopt Bayesian theory to depict the demand updating. At the same time, we focus on the vaccine supply chain and aim to maximize social welfare in our study. However, different from them, we explore the vaccine supply chains under COVID-19 and explore specific factors such as the disease's infection rate, vaccine's efficacy level, cold chain requirement, etc.

Blockchain is commonly regarded as an efficient technological tool to achieve supply chain traceability and transparency (Ivanov et al. 2019, Hastig and Sodhi 2020, Chod et al. 2020, Babich and Hilary 2020, Choi et al. 2022). Blockchain adoption in supply chain management has got increasingly popular and critical in recent years. In prior literature, blockchain adoption has been examined in various industries, including healthcare (Agbo et al. 2019, Niu et al. 2021), agriculture (Kamble et al., 2020), and fashion (Pun et al., 2021). Remarkably, considering the importance of vaccine quality and safety in preventing infectious diseases, e.g., COVID-19, the value of blockchain adoption in vaccine supply chain management has been noticed and examined (Dutta et al. 2020, Pournader et al. 2020). Yong et al. (2020) design an intelligent blockchain-based system that helps resolve the problems of vaccine expiration and record fraud. The authors highlight the critical role of blockchain adoption in supporting vaccine traceability and smart contract functions. Similarly, Antal et al. (2021) present a blockchain-based vaccine system in which smart contracts are deployed to monitor and track the vaccines. Their results prove the efficiency of blockchain adoption in the vaccine system while indicating the potential risk brought by the estimated cost. The smart contract function of blockchain in the vaccine supply chain is also evaluated by Omar et al. (2021), in which the authors propose a generic framework and use blockchain technology to automate the contract process for the stakeholders. Unlike Antal et al. (2021), Omar et al. (2021) demonstrate that their proposed blockchain-based solution is economically feasible for the vaccine supply chain. Verma et al. (2021) interestingly combine blockchain technology

with unmanned aerial vehicles (UAVs) and fifth-generation (5G) communication services in a vaccine supply chain. They find that their proposed system can provide a timely distribution process during the pandemic. Liu et al. (2021) establish a game-theoretical model to explore the pricing and coordination challenges in a vaccine supply chain comprising a vaccine manufacturer and a blockchain-based vaccine service platform. Their findings imply that blockchain implementation can enhance both the welfare and profit of the vaccine supply chain. Despite several papers examining blockchain adoption in the vaccine supply chain, none of them works on the value of blockchain adoption for vaccine ordering policy and its impact on social performance. This paper fills the respective gap.

3 **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., $e_n = 0$, 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 [1]. 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 will lead 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 $\bar{m}$, 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: $m \sim Normal(\mu_1, d_1)$. 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 modeling 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. 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 γ (

> 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., 2022), and its rationale 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., $v-\gamma-r(1-(1-G(t))e_n) > -r$. 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 1 for consumer partitions). Then, scaled by the potential market size $\bar{m}$, we derive the (random) demand for vaccines in the market as $\bar{m}(1-\gamma+r(1-G(t))e_n)$.

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. [2] 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 $D_1 \mid m \sim Normal(m(1-\gamma+r(1-G(t))e_A), \delta)$. Since in our model, $m \sim Normal(\mu_1, d_1)$, the unconditional distribution of D_1 is given by $D_1 \sim Normal(\mu_1(1-\gamma+r(1-G(t))e_A), \sigma_1^2)$, where $\sigma_1^2 \equiv \delta^2 + (1-\gamma+r(1-G(t))e_A)^2 d_1^2$. 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 $m \mid \omega \sim Normal(\mu_2, d_2)$ 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 :

$x_2 \equiv D_2 \mid \mu_2 \sim Normal(\mu_2(1-\gamma+r(1-G(t))e_n), \sigma_2^2)$, 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 subsection 3.1. 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 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 A1 in Online Appendix B.

In the basic model, we assume that the disease has the same infection rate (*r*) in two stages. This setting represents the case where there is no variant of the COVID-19 virus, which usually happens at the early pandemic stage, e.g., before September 2020 (WHO, 2022). Considering the real-world observation that the COVID-19 pandemic has started to mutate and generate a new variant of the virus after September 2020, we further consider the case where the disease's infection rate is different in two stages, i.e., r_1 in Stage 1 and r_2 in Stage 2. To save space, the corresponding contents can be formed in Online Appendix C, which provides similar findings to the ones in the basic model, and shows the robustness of our study. Moreover, we do not consider the loss of vaccine efficacy caused by the holding time. Hence Supplier A's vaccines have the same efficacy level in the two periods. We explain the rationality of this setting as follows: (i) In practice, the transportation of vaccines includes more uncontrollable situations (e.g., temperature, leakproofness) compared with the daily storage (i.e., holding time), which means that the efficacy of a vaccine is influenced more by the shipping time. (ii) We consider a significantly high holding cost (P.S.: higher than the shipping cost normalized to zero). This setting ensures the efficacy of the vaccine during the holding time. (iii) We want to reduce the "moving parts" and focus on the core. If we consider the situation in which the efficacy of vaccines depends on holding time, the mutual influences between the vaccine efficacy level and demand will exist.

To improve presentation, we let $\phi(\cdot)$ 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 $\Psi(a) = \int_a^{\infty} (x-a)\mathrm{d}\Phi(x)$. We define $f(\cdot)$ as the probability density function of its argument.

3.1 *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.

$$C_2^{AA} = E[(w_A + c)q_2 + h(q_1 + q_2 - D_2)^+], \quad (1)$$

$$CS_2^{AA} = E[(v - \gamma - r(1 - (1 - G(t))e_A))min?(D_2, q_1 + q_2) + (-r)(q_1 + q_2 - D_2)^-]. \quad (2)$$

Since under the pandemic, social welfare should be prioritized when the government makes decisions (Ivanov and Dolgui, 2020), we set social welfare in (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 operations management (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) and Xu et al. (2022), we define {The chance of infection transmission}={infection probability}× {number of people}. Then, as we can observe from the consumer surplus functions (e.g., $CS_2^{AA} = E[(v - \gamma - r(1 - (1 - G(t))e_A))min(D_2, q_1 + q_2) + (-r)(q_1 + q_2 - D_2)^-]$), if more people are vaccinated (i.e., $min(D_2, q_1 + q_2)$ is larger and $(q_1 + q_2 - D_2)^-$ is smaller), the consumers are more benefited as the infection transmission is lower (i.e., $r(1 - (1 - G(t))e_A)min(D_2, q_1 + q_2) + r(q_1 + q_2 - D_2)^-$ is smaller). Therefore, we believe that the objective functions set in our model are reasonable.

$$SW_2^{AA}(q_2 \mid \mu_2, q_1) = CS_2^{AA} - C_2^{AA}. \quad (3)$$

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 Online Appendix A.

Proposition 1

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

Proposition 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:

$$\begin{aligned} SW_1^{AA}(q_1 \mid \mu_1) &= \int_{-\infty}^{\frac{q_1-\sigma_2\Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_A}} E[SW_2^{AA}(q_2^{AA*}=0 \mid \mu_2, q_1)]\, f(\mu_2)\mathrm{d}\mu_2 \\ &+ \int_{\frac{q_1-\sigma_2\Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_A}}^{+\infty} E[SW_2^{AA}(q_2^{AA*}>0 \mid \mu_2, q_1)]\, f(\mu_2)\mathrm{d}\mu_2 - w_A q_1. \end{aligned} \tag{4}$$

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 $E[SW_2^{AA}(q_2^{AA*}=0 \mid \mu_2, q_1)]$ and $E[SW_2^{AA}(q_2^{AA*}>0 \mid \mu_2, q_1)]$ are:

$$\begin{aligned} &E[SW_2^{AA}(q_2^{AA*}=0 \mid \mu_2, q_1)] \\ &= \int_{-\infty}^{q_1} (v-\gamma-r(1-(1-G(t))e_A))x_2 f(x_2)\mathrm{d}x_2 \\ &+ \int_{q_1}^{+\infty} (v-\gamma-r(1-(1-G(t))e_A))q_1 f(x_2)\mathrm{d}x_2 - \int_{q_1}^{+\infty} r(x_2-q_1) f(x_2)\mathrm{d}x_2 \\ &+ \int_{-\infty}^{q_1} (-h)(q_1-x_2) f(x_2)\mathrm{d}x_2 \\ &= K_A[m_A - \sigma_2\Psi(\frac{q_1-m_A}{\sigma_2})] - rm_A - hq_1, \text{and} \end{aligned} \tag{5}$$

$$\begin{aligned} &E[SW_2^{AA}(q_2^{AA*}>0 \mid \mu_2, q_1)] \\ &= \int_{-\infty}^{m_A+\sigma_2\Phi^{-1}(s)} (v-\gamma-r(1-(1-G(t))e_A))x_2 f(x_2)\mathrm{d}x_2 \\ &+ \int_{m_A+\sigma_2\Phi^{-1}(s)}^{+\infty} (v-\gamma-r(1-(1-G(t))e_A))(m_A+\sigma_2\Phi^{-1}(s)) f(x_2)\mathrm{d}x_2 \\ &- \int_{m_A+\sigma_2\Phi^{-1}(s)}^{+\infty} r[x_2-m_A-\sigma_2\Phi^{-1}(s)] f(x_2)\mathrm{d}x_2 \\ &+ \int_{-\infty}^{m_A+\sigma_2\Phi^{-1}(s)} (-h)(m_A+\sigma_2\Phi^{-1}(s)-x_2) f(x_2)\mathrm{d}x_2 - (w_A+c)[m_A+\sigma_2\Phi^{-1}(s)-q_1] \\ &= (K_A-r)m_A - (h+w_A+c)[m_A+\sigma_2\Phi^{-1}(s)] - K_A\sigma_2\Psi(\Phi^{-1}(s)) + (w_A+c)q_1. \end{aligned} \tag{6}$$

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 $SW_1^{AA}(q_1 \mid \mu_1)$. We define:

$$z_A = \frac{q_1 - \sigma_2 \Phi^{-1}(s)}{1 - \gamma + r(1 - G(t))e_A},$$

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

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

$$+(-h + K_A - w_A - c)\Phi[\frac{z_A - \mu_1}{\sqrt{d_1^2 / (d_1 + \delta)}}] + c.$$

Lemma 1

(i) The expected benefit-to-go in Stage 1, $SW_1^{AA}(q_1 \mid \mu_1)$ 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

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

$$r \le \frac{w_A + c - 1/2 + \gamma - c/\Phi[\frac{z_A - \mu_1}{\sqrt{d_1^2 / (d_1 + \delta)}}]}{(1 - G(t)e_A)}, \text{ then } q_1^{AA*} = 0.$$

Lemma 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.

3.2 *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 (9).

$$C_2^{AB} = E[(w_B + c)q_2 + h(q_1 + q_2 - D_2)^+], \quad (7)$$

$$CS_2^{AB} = \begin{cases} E[(v-\gamma-r(1-(1-G(t))e_A))min(D_2,q_1) + \\ (v-\gamma-r(1-(1-G(t))e_B))min((D_2-q_1)^+,q_2) - r(q_1+q_2-D_2)^-], & \text{if } e_A > e_B \\ E[(v-\gamma-r(1-(1-G(t))e_A))min((D_2-q_2)^+,q_1) + \\ (v-\gamma-r(1-(1-G(t))e_B))min(D_2,q_2) - r(q_1+q_2-D_2)^-], & \text{if } e_A \le e_B, \end{cases} \quad (8)$$

$$SW_2^{AB}(q_2 \mid \mu_2, q_1) = CS_2^{AB} - C_2^{AB}. \quad (9)$$

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 $n = \begin{cases} A, & \text{if } e_A > e_B \\ B, & \text{if } e_A \le e_B \end{cases}$,

$s = \begin{cases} \dfrac{1-2(\gamma+w_B+c-r(1-G(t))e_B)}{1+2(h-\gamma+r(1-G(t))e_B)}, & \text{if } e_A > e_B \\ \dfrac{1-2(\gamma+w_B+c-r(1-G(t))e_B)}{1+2(h-\gamma+r(1-G(t))e_A)}, & \text{if } e_A \le e_B \end{cases}$, and s represents the inventory service level of the vaccine in Stage 2. The derivations of optimal decisions are available in Online Appendix A.

Proposition 2

(i) When $\mu_2 > \bar{\mu}^{AB}$ *,we have* $q_2^{AB*} > 0$ *; when* $\mu_2 \le \bar{\mu}^{AB}$*, we have* $q_2^{AB*} = 0$*, where* $\bar{\mu}^{AB} = \dfrac{q_1 - \sigma_2\Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_n}$*. (ii) If* $e_A > e_B$*,* $\bar{\mu}^{AB}$ *is decreasing in* e_A *and* e_B*; while if* $e_A \le e_B$*,* $\bar{\mu}^{AB}$ *is increasing in* e_A *and decreasing in* e_B

Proposition 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 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:

$$\begin{aligned} SW_1^{AB}(q_1 \mid \mu_1) = & \int_{-\infty}^{\frac{q_1-\sigma_2\Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_n}} E[SW_2^{AB}(q_2^{AB*}=0 \mid \mu_2, q_1)]\, f(\mu_2)\mathrm{d}\mu_2 \\ & + \int_{\frac{q_1-\sigma_2\Phi^{-1}(s)}{1-\gamma+r(1-G(t))e_n}}^{+\infty} E[SW_2^{AB}(q_2^{AB*}>0 \mid \mu_2, q_1)]\, f(\mu_2)\mathrm{d}\mu_2 - w_A q_1, \end{aligned} \quad (10)$$

where $n = \begin{cases} A, & \text{if } e_A > e_B \\ B, & \text{if } e_A \le e_B \end{cases}$, $s = \begin{cases} \dfrac{1-2(\gamma + w_B - r(1-G(t))e_B)}{1+2(h-\gamma+r(1-G(t))e_B}, & \text{if } e_A > e_B \\ \dfrac{1-2(\gamma + w_B - r(1-G(t))e_B)}{1+2(h-\gamma+r(1-G(t))e_A}, & \text{if } e_A \le e_B \end{cases}$.

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

$$\begin{aligned} &E[SW_2^{AB}(q_2^{AB*} = 0 \mid \mu_2, q_1)] = E[SW_2^{AA}(q_2^{AA*} = 0 \mid \mu_2, q_1)] \\ &= K_A[m_A - \sigma_2\Psi(\frac{q_1 - m_A}{\sigma_2})] - rm_A - hq_1, \text{and} \end{aligned} \tag{11}$$

if $e_A > e_B$,

$$\begin{aligned} &E[SW_2^{AB}(q_2^{AB*} > 0 \mid \mu_2, q_1)] \\ &= \int_{-\infty}^{q_1}(v-\gamma-r(1-(1-G(t))e_A))x_2 f(x_2)dx_2 + \int_{q_1}^{+\infty}(v-\gamma-r(1-(1-G(t))e_A))q_1 f(x_2)dx_2 \\ &+\int_{-\infty}^{m_A+\sigma_2\Phi^{-1}(s)}(v-\gamma-r(1-(1-G(t))e_B))(x_2-q_1)f(x_2)dx_2 \\ &+\int_{m_A+\sigma_2\Phi^{-1}(s)}^{+\infty}(v-\gamma-r(1-(1-G(t))e_B))q_2 f(x_2)dx_2 - \int_{m_A+\sigma_2\Phi^{-1}(s)}^{+\infty} r[x_2 - m_A - \sigma_2\Phi^{-1}(s)]f(x_2)dx_2 \\ &-\int_{-\infty}^{m_A+\sigma_2\Phi^{-1}(s)} h(m_A+\sigma_2\Phi^{-1}(s)-x_2)f(x_2)dx_2 - (w_B+c)[m_A+\sigma_2\Phi^{-1}(s)-q_1] \\ &= (K_A - h - r)[m_A - \sigma_2\Psi(\frac{q_1-m_A}{\sigma_2})] + (K_B - h - r - w_B - c)(m_A - q_1) \\ &-(h+w_B+c)\sigma_2\Phi^{-1}(s) - K_B\sigma_2\Psi(\Phi^{-1}(s)); \end{aligned}$$

(12)

while if $e_A \le e_B$,

$$
\begin{aligned}
&E[SW_2^{AB}(q_2^{AB*} > 0 \mid \mu_2, q_1)] \\
&= \int_{-\infty}^{m_B+\sigma_2\Phi^{-1}(s)} (v-\gamma-r(1-(1-G(t))e_A))(x_2-q_2)\,f(x_2)\mathrm{d}x_2 \\
&+ \int_{m_B+\sigma_2\Phi^{-1}(s)}^{+\infty} (v-\gamma-r(1-(1-G(t))e_A))q_1\,f(x_2)\mathrm{d}x_2 \\
&+ \int_{-\infty}^{m_B+\sigma_2\Phi^{-1}(s)-q_1} (v-\gamma-r(1-(1-G(t))e_B))x_2\,f(x_2)\mathrm{d}x_2 \\
&+ \int_{m_B+\sigma_2\Phi^{-1}(s)-q_1}^{+\infty} (v-\gamma-r(1-(1-G(t))e_B))q_2\,f(x_2)\mathrm{d}x_2 - \int_{m_B+\sigma_2\Phi^{-1}(s)}^{+\infty} r[x_2-m_B-\sigma_2\Phi^{-1}(s)]\,f(x_2)\mathrm{d}x_2 \\
&- \int_{-\infty}^{m_B+\sigma_2\Phi^{-1}(s)} h(m_B+\sigma_2\Phi^{-1}(s)-x_2)\,f(x_2)\mathrm{d}x_2 - (w_B+c)[m_B+\sigma_2\Phi^{-1}(s)-q_1] \\
&= (K_A-h-r)[q_1-\sigma_2(\Phi^{-1}(s)+\Psi(\Phi^{-1}(s)))] + (K_B-h-r)(m_B-\sigma_2\Psi(\frac{\sigma_2\Phi^{-1}(s)-q_1}{\sigma_2})) \\
&-(h+r)\sigma_2\Psi(\Phi^{-1}(s)) - (h+w_B+c)\sigma_2\Phi^{-1}(s) - (m_B-q_1)(w_B+c).
\end{aligned}
$$

(13)

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

Lemma 2

(i) The expected benefit-to-go in Stage 1, $SW_1^{AB}(q_1 \mid \mu_1)$ *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* $r \le \bar{r}$, *then* $q_1^{AB*} = 0$.

We argue that the holding cost condition in Lemma 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 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 1.

Theorem 1

In Stage 1, determine q_1^{AA*} *(or* q_1^{AB*}*) by checking the decision rule proposed in Lemma 1 (or Lemma 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* $q_2^{AA*} = max\{0, \mu_2[1-\gamma+r(1-G(t))e_A] + \sigma_2\Phi^{-1}(s) - q_1^{AA*}\}$ *(or* $q_2^{AB*} = max\{0, \mu_2[1-\gamma+r(1-G(t))e_n] + \sigma_2\Phi^{-1}(s) - q_1\}$, *where* $n = \begin{cases} A, & \text{if } e_A > e_B \\ B, & \text{if } e_A \le e_B \end{cases}$*).*

4 **Decision Analysis**

In Section 3, we have analytically derived the government's optimal two-stage vaccine ordering decisions with information updating. In this section, 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.

4.1 *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 A2 to A8 are in Online Appendix B.

Observation 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 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 Section 5.1.

4.2 *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 A9 to A15 in Online Appendix B.

Observation 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 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 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 A1 in Online Appendix B. 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 2 .

4.3 *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 $\overline{w_A} = \arg_{w_A}\{\frac{1-2(\gamma + w_A - r(1-G(t))e_A)}{1+2(h-\gamma + r(1-G(t))e_A)} = \frac{1-2(\gamma + w_B - r(1-G(t))e_B)}{1+2(h-\gamma + r(1-G(t))e_B)}\}$ and

$$\overline{\mu_2} = \frac{\sigma_2[\Phi^{-1}(\frac{1-2(\gamma + w_A - r(1-G(t))e_A)}{1+2(h-\gamma + r(1-G(t))e_A)}) - \Phi^{-1}(\frac{1-2(\gamma + w_B - r(1-G(t))e_B)}{1+2(h-\gamma + r(1-G(t))e_A)})]}{r(1-G(t))(e_B - e_A)}.$$

Proposition 3

For given q_1, *if* $e_A > e_B$, *then* $q_2^{AA*} < q_2^{AB*}$ *if and only if* $w_A > \overline{w_A}$; *while if* $e_A \le e_B$, *then* $q_2^{AA*} < q_2^{AB*}$ *if and only if* $\mu_2 > \overline{\mu_2}$.

Proposition 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 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* $e_A \le e_B$, *social welfare is higher in Case AA if r is relatively large; otherwise, social welfare is higher in Case AB.*

Observation 3 guides the government's vaccine selection decision under the pandemic. Details of the numerical settings can be found in Figure A16 in Online Appendix B. 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 prefered 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 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 2 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 1 and 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 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 Online Appendix A). 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.

5 **Extensions**

5.1 *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 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 subsection, 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, on 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 (Xu et al., 2022). 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 Online Appendix A. 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 4. All the results and proofs can be found in Online Appendix A.

Proposition 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* $G(t) > \frac{\sigma_2[\Phi^{-1}(s) - \Phi^{-1}(s^{BT})]}{\mu_2 re_A}$, *otherwise,* $q_2^{BT,AA*} \le q_2^{AA*}$.

Proposition 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 $\Delta SW_1^i = SW_1^{BT,i}(q_1 \mid \mu_1) - SW_1^i(q_1 \mid \mu_1)$ as the value of blockchain adoption in terms of social welfare, where $i = AA$ or *AB*. We then conduct numerical analysis and yield Observation 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 A17) are shown in Online Appendix B.

Observation 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.,* $\Delta SW_1^{AB} < 0$*) 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 4 presents the value of blockchain adoption in different cases. The results in Observations 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 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.

5.2 *Ordering policy considering the side effects*

In this subsection, 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. Centers 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 $v - \gamma - r(1 - (1 - G(t))e_n) - L_n]$. Therefore, the vaccine demand is realized as $\bar{m}[1 - \gamma + r(1 - G(t))e_n - L_n]$.

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

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

Proposition 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* $\mu_2 \le \bar{\mu}^{SE,i}$, *we have* $q_2^{SE,i*} = 0$, *where* $\bar{\mu}^{SE,i} = \dfrac{q_1 - \sigma_2\Phi^{-1}(s^{SE})}{1-\gamma+r(1-G(t))e_n - L_n} > \bar{\mu}^i$, *and* $n = \begin{cases} A, & \text{if } i = AA \text{ or } (i = AB \text{ and } e_A > e_B) \\ B, & \text{if } i = AB \text{ and } e_A \le e_B \end{cases}$.

Proposition 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 Online Appendix A). 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 A18 in Online Appendix B) and obtain Observation 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

(i) When r is relatively small, social welfare is higher in Case AA if $e_A \le e_B$ *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 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 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.

6 **Conclusion**

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).

Although our study has provided managerial insights which help the government to set its optimal vaccine ordering policy under COVID-19, we admit some limitations. First, the M-stage/M-supplier (M¿2) problem is practical while it is difficult to derive the analytically tractable closed-form solutions, which is critically important for an analytical modeling paper. Hence, for future research, other optimization methods like stochastic programming can be adopted to extend our findings under a multi-stage/multi-supplier ordering framework (Kaminsky and Wang, 2019). Second, the loss of vaccine efficacy caused by the holding time is ignored in this study, and we assume that the use of blockchain can perfectly eliminate the loss of efficacy during transportation, irrespective of shipping time. For future studies, it will be meaningful to explore the case when time plays a role, even though a totally different model should be established (e.g., a continuous time model in which the efficiency of blockchain depends on time). Third, we may consider an alternative Bayesian model where both the mean and variance of the customer population are unknown and can be updated in the second stage (Choi et al., 2006). Finally, it will be interesting to explore further the impacts of supply disruption on the government's decisions, as it is a critical issue faced by most manufacturers during the pandemic (Ivanov, 2020; Xu et al., 2023).

Acknowledgements

We are indebted to the editors and reviewers for their critical and important comments. This paper is a part of the first author's doctoral thesis research, and the research idea and model are co-developed by Tsan-Ming Choi and Xiaoyan Xu. All co-authors have important contributions, and the authorship listing follows a reversed alphabetical order. Xiaoyan Xu's research is fully supported by The Hong Kong Polytechnic University under the account code RK38. Tsan-Ming Choi is the corresponding author.

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Notes

[1] 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.

[2] 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.

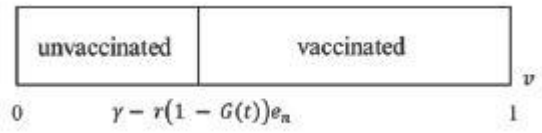

Figure 1: Consumer partitions of vaccination behavior.

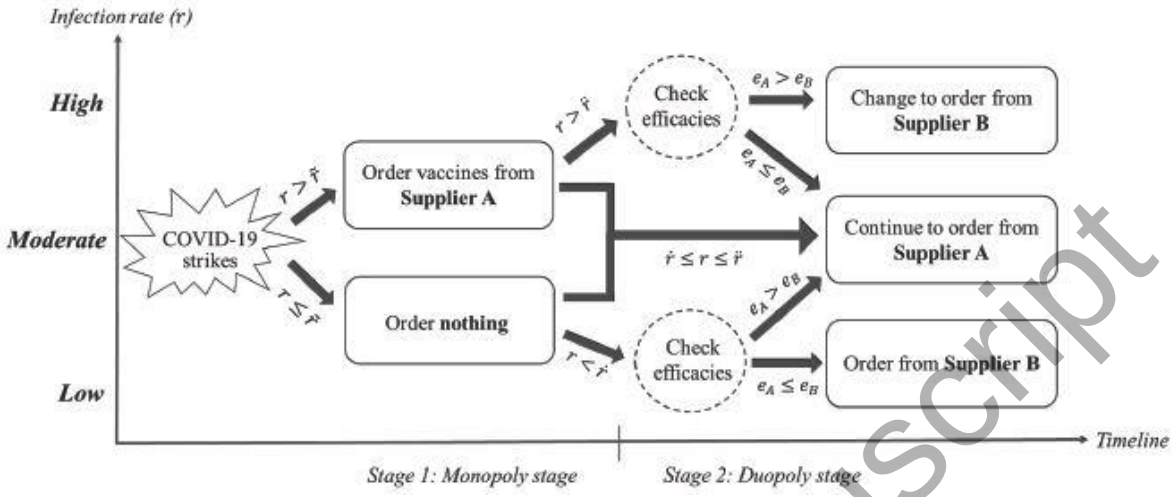

Figure 2: The government's optimal vaccine ordering policy under the pandemic (Remarks: $\tilde{r}$ and $\dot{r}$ are increasing in the shipping time *t*; $\ddot{r}$ is decreasing in *t*).

Table 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

Table 2: Summary of Sensitivity Analyses

Sensitivity Analyses for q_1^*				
	r	e A	e B	t
Case AA	↑	↑	N/A	↓
Case AB			↓	
Sensitivity Analyses 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 ≤ 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. .