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Estimating the economic loss of a seaport due to the impact of COVID-19
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A B S T R A C T
Sea ports are key nodes of global trade and economy, but are vulnerable to hazards, catastrophes and epidemic outbreaks. Since the emergence of COVID-19 infection at the end of 2019, the operations of seaports, especially container ports have been hit hard. This paper aims to explore the impacts of COVID-19 on container ports’ operations, clarify the potential economic losses of ports and propose coping suggestions for recovery. Five scenarios of port recovery have been set and the revenues of the port under epidemic outbreaks are estimated. The economic loss could be modeled as the difference between original revenue a port should obtained without the impact of COVID-19 and the actual revenue considering the impact of COVID-19. The container port of Shanghai is selected as the case study. Results and sensitivity analysis reveal that slower the recovery develops, much more loss will be borne by the port. However, there is also a possibility that the port achieves increased income with a surging boom of shipping demand. The loss of port due, handling service, facility security fee and berthing charge are major losses. Besides, port handling efficiency and fleet structure are also found crucial for reducing economic losses. Reducing containership’s handling time and serving larger ships would also help the port reduce economic losses.

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1. Introduction
Within the globalized economy and international supply chain, seaports are acting as critical nodes that help facilitate international shipping and trade (Zhang and Lam, 2016). Besides, as the shipping industry contributes nearly 90% of the global trade volume (Dai et al., 2019), this indicates that the stability of port operations is extremely crucial for international trade. However, according to Sanchez-Rodrigues et al. (2010), port is regarded as one of the most uncertain components within the global supply chain due to its vulnerability to external shocks. According to Chopra and Sodhi (2004), port disruption is one of the key threats affecting the overall resilience of the global supply chain. A port disruption is defined as an event which could cause a sudden interruption on material flow in the transport system and may lead to a stoppage in cargo movement (Wilson, 2007). Usually, such kinds of events would be classified as natural hazards (e.g. typhoons, earthquakes), man-made catastrophes (e.g. chemical plant explosions, terrorist attacks) or strikes of port workers (Hosseini et al., 2019). However, there is another kind of event which could bring severe impacts to the port, which is the epidemic outbreak. In contrast to other disruption events, epidemic outbreak has its unique characteristics as: (1) the existence of epidemic outbreak is usually longer than other events, and the impacts on ports and the whole supply chain is long-term, (2) epidemic outbreak impose disruptions on all the parties and nodes on the supply chain, and (3) the disruption propagation of epidemic outbreak is simultaneous across the overall supply chain (Ivanov, 2020; Xu et al., 2021a,b).

The recent coronavirus (COVID-19/SARS-CoV-2) outbreak came from Wuhan area, China and immediately impacted Chinese exports and drastically reduced the supply availability in global SCs. Araz et al. (2020) underline that the COVID-19 outbreak represents one of the major disruptions encountered during the last decades which is “breaking many global supply chains”. In the period from January 20th to February 5th, 2020 the number of confirmed cases of coronavirus in China rose from 292 to 28,018 cases with a further increase to 80,880 cases as on March 16 (Worldometer, 2020). In the last decade of February and early in March 2020, the number of COVID-19 cases has exponentially increased in Asia, Europe and USA resulting in border closures and quarantines. On March 11, 2020, the World Health Organization (WHO) announced the pandemic given more than 1,18,000 COVID-19 cases confirmed worldwide.

The outbreak has nearly caused a halt to the whole country of China at the beginning of year 2020 and the domestic economic
activities have all been affected. The manufacturing industries and exports of China were heavily hurt and the global supply chain was severely affected in turn. As critical nodes within the global trade, the disruption of ports reinforces the failures on global supply chain, especially in the beginning of the COVID-19 outbreak, for safety concerns that some ports were unavailable to accommodate calling foreign ships. Since then with the global dispersion of COVID-19, more and more international ports are unable to provide full services and most of the ports are suffering from economic losses. In such a turbulent environment, the firms facing the epidemic outbreaks have a series of common questions to ask, i.e., how long can a supply chain sustain a disruption, how long does it take for a supply chain to recover after an epidemic outbreak, which operating policy is the most efficient to cope with disruptions at different levels of severity of the epidemic dispersal? A large body of past research has paid certain attention on port disruption risk analysis and management, while little has been done on assessing the economic impacts of port disruptions. Clearly identifying the potential impact duration and assessing the economic losses of ports under the strike of COVID-19 is crucial for policy makers and port authorities dealing with the current dilemma and making future port recovery decisions. Some existing research has investigated the economic losses of ports under natural hazards (e.g. typhoon), hence there is a relatively strong demand for establishing an economic loss assessment framework of ports under COVID-19 outbreak.

With the aim to address this research demand, this paper targets to propose a framework to quantify the economic losses of ports due to the epidemic. Furthermore, the port of Shanghai is selected as a case to demonstrate the proposed scheme, in which the numerical analysis will be done based on the assumption of different recovery speed. And the sensitive analysis follows in order to test the effect of the policies. The research road map of this article is shown in Fig. 1.

2. Literature review

The stability in port operations is the key factor in facilitating the international trade market. It is reported that maritime transport contributes 90% of the world trade volume which implies its crucial role in providing various kinds of shipping services and thus has a very close relationship with the related industries (Lam and Yap, 2011). As a result, risks and uncertainties in ports are considered as important issues in port management research (Mokhtari et al., 2012). Factors including climate extremes, security, social stability, and political stability need to be fully analyzed in the risk management for port planning and operations.

Being a platform linking the sea and inland transportation, a port and its stakeholders are much affected by any port disruption. Disruptions, being one of the risks, include a wide coverage of events that lead to a halt in cargo and trade flows (Kleindorfer and Saad, 2005). Basically, port disruption events can be classified into man-made events (e.g. terrorist acts) and natural calamities (Stecke and Kumar, 2009). One should note that there is a difference between delay and disruption. Both delay and disruption will postpone the time of arrival of the products (Omer et al., 2012) but disruption stops the flow entirely while delay refers to a slower flow rate. The consequence of a port disruption could be disastrous. The influence is usually international and the impact may spread to many aspects in the society: political, environmental, economic, etc. Chang (2000) has found that an earthquake-induced port disruption could lead to a loss of share of transshipment traffic. The economic impacts of port disruption resulted from terrorist attacks have been discussed by Park et al. (2008). The propagation of the port disruption risks to the other industrial factors has also been discussed by Peck (2006). Generally, there are two key observations from the literature. Firstly, the consequence of a disruption can sometimes be irreversible for the affected port. Secondly, the port and the port network as a whole can be designed to be more adaptive to
adverse situations. It is thus crucial to understand how a port is affected by disruptions, in order to develop strategies and policies to maintain its capacity and resilience.

Comprehensively considering the international public health emergencies, Shao et al. (2019) conclude that the epidemic will cause traffic interruption, which affects tourism and consumer confidence; foreign economic exchanges are interrupted, and foreign trade activities of some foreign trade companies in areas with severe epidemics are all interrupted; Chinese commodity orders are reduced. During SARS in 2003, negotiations on linear contracts are blocked, manufacturing is shut down, and relevant port quarantine measures have become more complicated, affecting linear timeliness and reducing export orders (You, 2003). In 2014, under the influence of Ebola, ships in the affected countries were prohibited from docking or required advance reporting and approval, and ships were unwilling to carry out related voyages in the affected countries (Liu, 2014). All the factors mentioned above deserve the attention when studying the impact of COVID-19 on ports.

More specific studies on the economic assessment methodology related to ports are referred to for this research. By now there are three major models for port economic impact analysis, which are input output model, gravity model and computable equilibrium model. Zhang and Lam (2015) develop an approach of estimating the economic losses of port disruptions induced by extreme wind events in which the total economic loss is split into four parts including reputational loss, loss to the shippers, loss to the carriers and loss to the ports. Besides, Zhang and Lam (2016) also develop a systematic framework for performing economic loss estimation of industry clusters due to port disruptions based on the establishment of a network flow model, considering both effects on the inbound and outbound supply chains. By analyzing the characteristics of the import and export cargos of Shenzhen port which is the case, the economic losses are further classified into four different kinds, namely, direct loss in the import of raw materials, loss of delay in the import of raw materials, direct loss in the export of products and loss of delay in the export of products. It is clear that the hierarchy structure is helpful when calculating the total economic losses of a complex object.

To summarize the literature review, most of the researches focus on the entirety or combination where a port is an auxiliary element, while quite few ones pay attention to the port itself. However, it is better for policy makers to prescribe the right medicine focusing on a small entry point when making decisions. Therefore, there is an urgent demand to build a detailed and explicit framework to quantify the port economic losses.

3. Model formulation

Zhang and Lam (2015, 2016) generally classified the economic loss of the shipping supply chain into the categories of reputational loss and physical loss of import and export. Thus, in this article, we follow the rationale of the classification, and the economic loss of a port is classified into two parts: direct loss and indirect loss. In details, direct loss consists of port service loss, berthing service loss and handling service loss. While indirect loss mainly refers to reputational loss during the epidemic time. The detailed structure is port economic loss is presented in Fig. 2.

During the COVID-19 epidemic outbreak, the entire global shipping market has been affected, though different types of shipping sub-markets suffered different degrees due to the characteristics of the cargoes they transported and the operational features. As a typical global business, container shipping is one of the most affected services under COVID-19 epidemic outbreak with the shutting down of many manufacturing bases in major export countries, such as China. Unlike container shipping, tanker shipping enjoyed a boom as we witnessed a sharp increase in oil price. So, to better capture the negative impacts of a port suffered under the COVID-19 infection and estimate the potential economic losses, container shipping is selected as the case for economic loss estimation in this research.

In this article, based on the hierarchy structure of the port economic loss, we will first clarify the formulation of each loss segment and sort out all the calculation factors with the classification of constants and variables. Next, we can determine the value of the constants and use proper method to analyze the variables, including forecasting and scenario setting. Then, we can input the data and get the results. Finally, we can also do the sensitivity analysis for certain parameters of the formulations and get the conclusion and recommendations.

3.1. Estimation of direct loss

Direct loss means the immediate monetary loss of closed port-provided service due to the outbreak of COVID-19. Considering the kinds of service that a port provides, direct loss is classified into 3 sub-segments as: port service loss, berthing service loss and handling service loss (https://www.portshanghai.com.cn).

Port service includes the service of port dues, port facility security and oil containment boom usage. Thus, port service loss indicates the immediate economic loss of those service charges that could have been charged to the shippers or shipowners. Berthing service includes the service of pilotage, towage and berthage. Berthing service loss indicates the immediate economic loss of those service fees that could have been charged to the payers. Handling service mainly refers to terminal handling service, so handling service loss indicates the immediate economic loss of terminal handling charge to containerships or bulk carriers.

The formulation of the direct loss of a port ($L_{\text{dir}}$) could be modeled as follows:

$$L_{\text{dir}} = R_0 - R = L_{\text{ps}} + L_{\text{hs}} + L_{\text{bs}}$$  \hspace{1cm} (1)

where:

- $R_0$: the total revenue of the port regardless of the impact of COVID-19
- $R$: the total revenue of the port under the impact of COVID-19
- $L_{\text{ps}}$ is the loss of port service charge
- $L_{\text{hs}}$ is the loss of berthing service charge
- $L_{\text{bs}}$ is the loss of handling service charge

3.1.1. Estimation of loss of port service charge ($L_{\text{ps}}$)

Basically, the economic loss of a specific kind of service should be estimated by calculating the difference between the revenue of the service regardless of the emergence of the COVID-19 outbreak (that is the original revenue under the business as usual (BAU) scenario) and the revenue of the service during the epidemic outbreak. So, the loss of port service charge could be modeled as follows:

$$L_{\text{ps}} = R_{\text{ps,0}} - R_{\text{ps}} = L_{\text{pd}} + L_{\text{fs}} + L_{\text{bu}}$$  \hspace{1cm} (2)

where:

- $R_{\text{ps,0}}$ is the original revenue of port service regardless of the impact of COVID-19
- $R_{\text{ps}}$ is the estimated revenue of port service considering the impact of COVID-19
- $L_{\text{pd}}$ is the loss of port dues
- $L_{\text{fs}}$ is the loss of port facility security fee
- $L_{\text{bu}}$ is the loss of oil containment boom usage fee

Furthermore, the port service charge is composed of port dues, port facility security fee and oil containment boom usage fee:

$$R_{\text{ps},0} = R_{\text{pd},0} + R_{\text{fs},0} + R_{\text{bu},0} = N_0 \cdot U \cdot r_{\text{pd}} \cdot T + N_0 \cdot U \cdot r_{\text{fs}} \cdot T$$
\[ R_{ps} = R_{ps,0} + R_{fs} + R_{bu} = N \cdot U \cdot r_{pd} \cdot T + N \cdot U \cdot r_{fs} \cdot T + N \cdot r_{bu} \cdot T \]
\[ + N \cdot r_{bu} \cdot T \]

where:
- \( R_{ps,0} \) is the original revenue of port dues regardless of the impact of COVID-19.
- \( R_{fs} \) is the estimated revenue of port facility security fee considering the impact of COVID-19.
- \( R_{bu} \) is the estimated revenue of oil containment boom usage fee considering the impact of COVID-19.

So, we could have
\[ L_{ps} = L_{ps,0} + L_{fs} + L_{bu} = \]
\[ N_0 \cdot U \cdot r_{pd} \cdot T + N_0 \cdot U \cdot r_{fs} \cdot T + N_0 \cdot r_{bu} \cdot T - N \cdot U \cdot r_{pd} \cdot T - N \cdot U \cdot r_{fs} \cdot T - N \cdot r_{bu} \cdot T = \]
\[ \Delta N \cdot U \cdot r_{pd} \cdot T + \Delta N \cdot U \cdot r_{fs} \cdot T + \Delta N \cdot r_{bu} \cdot T \]

where:
- \( N_0 \) is the average daily number of calling containerships regardless of the impact of COVID-19.
- \( N \) is the average daily number of calling containerships under the impact of COVID-19.
- \( \Delta N \) is the number gap between \( N_0 \) and \( N \) \((N_0 - N)\).
- \( U \) is the average size of containerships (fully-loaded) in TEUs.
- \( r_{pd} \) is the average port due rate in CNY/TEU for containerships.
- \( r_{fs} \) is the average port facility security fee rate in CNY/TEU for containerships.
- \( r_{bu} \) is the average oil containment boom usage fee rate in CNY per ship call.
- \( T \) is the total duration of the port that under the impact of COVID-19 of the port in days.

Specifically, the average ship size \( U \) of all the calling ships could be obtained as the sum of average size of each segment, as modeled in Eq. (6):
\[ U = \sum U_i \cdot P_i \cdot \text{If} \]

where:
- \( U_i \) is the average size of each vessel size segment.
- \( P_i \) is the percentage of the number of vessels in each size segment.
- \( i \) is the number of vessel size segments.
- \( \text{If} \) is the load factor, meaning the actual average loaded TEU as \% of vessel’s overall capacity.

### 3.1.2. Estimation of loss of berthing service charge (\( L_{bs} \))

Following the recipe, the loss of berthing service charge could be modeled as follows:
\[ L_{bs} = R_{bs,0} - R_{bs} = L_{pl} + L_{tw} + L_{bc} \]

where:
- \( R_{bs,0} \) is the original revenue of berthing service charge regardless of the impact of COVID-19.
- \( R_{bs} \) is the estimated revenue of berthing service charge considering the impact of COVID-19.

Similarly, the berthing service charge consists of pilotage fee, towage fee and berthing charge, so the berthing service loss can be got:
\[ R_{bs,0} = R_{pl,0} + R_{tw,0} + R_{bc,0} = N_0 \cdot W \cdot r_{pl} \cdot T + N_0 \cdot r_{tw} \cdot T + N_0 \cdot W \cdot r_{bc} \cdot T \cdot T_b \]
\[ = \]
\[ \Delta N \cdot W \cdot r_{pl} \cdot T + \Delta N \cdot W \cdot r_{bc} \cdot T \cdot T_b \]

where:
- \( R_{pl,0} \) is the original revenue of pilotage fee regardless of the impact of COVID-19.
- \( R_{pl} \) is the estimated revenue of pilotage fee considering the impact of COVID-19.
- \( R_{tw,0} \) is the original revenue of towage fee regardless of the impact of COVID-19.
- \( R_{tw} \) is the estimated revenue of towage fee considering the impact of COVID-19.
- \( R_{bc,0} \) is the original revenue of berthing charge regardless of the impact of COVID-19.
- \( R_{bc} \) is the estimated revenue of berthing charge considering the impact of COVID-19.

Obviously,
\[ L_{bs} = L_{pl} + L_{tw} + L_{bc} = \Delta N \cdot W \cdot r_{pl} \cdot T + \Delta N \cdot W \cdot r_{bc} \cdot T \cdot T_b \]

where:
- \( L_{pl} \) is the loss of pilotage fee.
- \( L_{tw} \) is the loss of towage fee.
- \( L_{bc} \) is the loss of berthing charge.
- \( W \) is the average net tonnage of containerships in tons.
- \( r_{pl} \) is the average pilotage fee rate in CNY/ton.
- \( r_{tw} \) is the average towage fee rate in CNY per ship call.
- \( r_{bc} \) is the average berthing charge rate in CNY/ton/day.
- \( T_b \) is the average berthing time in port in days.

### 3.1.3. Estimation of loss of handling service charge (\( L_{hs} \))

The handling service loss refers to the loss of terminal handling charge:
\[ L_{hs} = R_{hs,0} - R_{hs} \]

where:
Table 1
Illustration of port service classification and units.
Source: The port of Shanghai (https://www.portshanghai.com.cn/tjsj/index.jhtml).

| Description                  | Symbol | Unit       |
|------------------------------|--------|------------|
| Port service charge          |        |            |
| Port dues                    | \( l_{pd} \) | CNY/TEU   |
| Port facility security fee   | \( l_0 \)  | CNY/TEU   |
| Oil containment boom usage fee| \( l_{u0} \) | CNY/ship call |
| Berthing service charge      |        |            |
| Pilotage fee                 | \( l_{pr} \) | CNY/ton   |
| Towage fee                   | \( l_{tw} \) | CNY/ship call |
| Berthage charge              | \( l_{bc} \) | CNY/ton/day |
| Handing service charge       |        |            |
| Terminal handling charge     | \( l_{nh} \) | CNY/TEU   |

\( R_{hs,0} \) is the original revenue of handling service regardless of the impact of COVID-19.

\( R_{hs} \) is the estimated revenue of handling service considering the impact of COVID-19.

The handling service is easily estimated as

\[
R_{hs,0} = N_0 \cdot U \cdot r_{hs} \cdot T
\]

\[
R_{hs} = N \cdot U \cdot r_{hs} \cdot T
\]

Therefore,

\[
L_{hs} = \Delta N \cdot U \cdot r_{hs} \cdot T
\]

where:

\( r_{hs} \) is the average terminal handling fee rate in CNY/TEU for containerships.

The detailed port service classification and description is illustrated in Table 1.

3.1.4. Estimation of average daily number of calling containerships (\( N_0 \) & \( N \))

The key of estimating future economic losses of a container port is determining the difference between the value of the average daily number of calling containerships during the epidemic outbreak (\( N \)) and the value of the average daily number of calling containerships under the normal operation had not been the epidemic (\( N_0 \)).

For better estimating the value of \( \Delta N \), the formulation is modeled in this research as follows:

\[
\Delta N = N_0 - N = \frac{DCT_0}{U} - \frac{DCT}{U}
\]

where:

\( DCT_0 \) is the average number of daily container throughput in TEUs regardless of the impact of COVID-19.

\( DCT \) is the average number of daily container throughput in TEUs considering the impact of COVID-19.

Conventionally, port’s container throughput is often recorded and reported by some authorities on a quarterly basis, throughput data is also a key determinant of port due charge and handling service fee. Thus, based on data accessibility and model formation, the container throughput is selected as the variable determining the calling ship number. The average number of daily container throughput could be modeled as the value of port’s quarterly working days divided by quarterly container throughput:

\[
DCT = \frac{QCT}{120}
\]

\[
DCT_0 = \frac{QCT_0}{120}
\]

where:

\( QCT_0 \) is the average number of daily container throughput in TEUs regardless of the impact of COVID-19.

\( QCT \) is the average number of daily container throughput in TEUs considering the impact of COVID-19.

120: quarterly working days of a port is assumed to be 120.

Thus, the key of estimating \( \Delta N \) is to estimate the values of \( QCT_0 \) and \( QCT \) respectively.

3.1.4.1. Estimation of \( QCT_0 \)

The group of values of \( QCT_0 \) for each season is a classical time series as the data derives regardless of the sudden impact of COVID-19 based on previous research on port throughput estimation. So, time series estimation methodology with seasonal adjustment and long-term trend fitting will be applied in this research to capture the characteristics of container port’s quarterly throughput (\( QCT_0 \)) when not considering impacts of sudden epidemic outbreaks, such as the COVID-19 (Schulze and Prinz, 2009).

The Holt–Winters exponential smoothing method has been widely applied in the shipping and aviation industries to predict future demand, as it is capable making short-term or midterm prediction for a relatively large collection of time series with a trend and seasonal variation. (Dantas et al., 2017; Huan et al., 2020). Thus, the additive Holt–Winters seasonal exponential smoothing model is selected as the forecasting model in this research. The classical Holt–Winters methods are based on three smoothing equations—one for the level, one for trend, and one for seasonality (Hyndman et al., 2008).

The model of the time series \( y_t(t = 1, 2, \ldots, T) \) (denoting \( QCT_0 \) in each quarter) with linear trend and additive seasonality consists of the following four equations, with three basic smoothing formulations and one forecasting formulation (Makridakis et al., 1998):

\[
l_t = \alpha (x_t - s_{t-m}) + (1 - \alpha) (l_{t-1} + b_{t-1})
\]

\[
b_t = \beta (l_t - l_{t-1}) + (1 - \beta) b_{t-1}
\]

\[
s_t = \gamma (x_t - l_{t-1} - b_{t-1}) + (1 - \gamma) s_{t-m}
\]

\[
y_{t+h} = l_t + h\delta + s_{t+h-m}
\]

In the equations above, \( l_t \) is the estimate of the level at time \( t \) with a level smoothing coefficient \( \alpha \), \( b_t \) yields the slope estimate at time \( t \) with a trend smoothing coefficient \( \beta \) and \( s_t \) represents the seasonal factors at time \( t \) with a seasonal smoothing coefficient \( \gamma \). \( y_{t+h} \) is the forecast made at time \( t + h \), with \( h = 1, 2 \ldots \)

The constant \( m \) indicates the number of periods per year in the series of data studied, e.g. for quarterly data \( m = 4 \).

3.1.4.2. Estimation of \( QCT \)

For the estimation of \( QCT \), traditional estimation methodologies could not depict the characteristics and dynamics of the impacts brought by the COVID-19 outbreak. Hence, scenario-based analysis is applied to estimate \( QCT \) as characteristics of economic and industry developments always follow different types of recoveries under different policy scenarios.

The rationale of scenario analysis is to estimate the evolutions of \( QCT \) under different potential scenarios based on previous actual data. The parameter of quarterly container throughput year-on-year growth rate (\( \delta \)) is introduced in this research to better capture the dynamics of \( QCT \) under COVID-19 and estimate the quarterly value of \( QCT \). The value of \( \delta \) of each quarter is dynamic, which is based on the settings of different scenarios. The parameter \( \delta \) is designed to eliminate the effects of seasonal variations and is used to illustrate the relative rate of development of the current level of development as compared to that of the same period last year. For scenario settings of shipping and port service recovery, we follow the assumptions of classical economic recovery scenarios of L-shaped, W-shaped and V-shaped, which are commonly used in recession periods (e.g. Hong and Tornell, 2005). When the value of \( \delta \) in the scenario analysis reaches a level comparable to the average growth rate in recent years, it is deemed that the situation has returned to normal and then the scenario analysis will be stopped. The details of the scenario setting are shown in Section 4.2.

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3.2. Estimation of indirect loss

Indirect loss refers to the potential economic loss might be borne by a port when the port is partly shut down or there is a delay of port service due to the outbreak of COVID-19. The potential occurrence of closed port or delayed port service might affect the expectations and confidence of cargo owners, carriers and other stakeholders. Zhang and Lam (2015) assumed that a port’s reputation would be hurt when a port disruption occurred due to natural hazards. Then under this circumstance, cargo owners and carriers may turn to other competitor ports.

While in this research, due to the global spread of COVID-19 infection, nearly all ports suffered from it. Thus, no single port would benefit from the reputational loss of its competitors and it is assumed that there will be no reputational loss to the ports during the spread of COVID-19.

Usually the disruption or shut down of a port due to natural hazards or infectious diseases would induce indirect economic losses to the port related supply chains and manufacturing clusters rather than the port itself. So, the indirect loss of a port during the outbreak of COVID-19 is not considered in this research.

4. Numerical analysis

As aforementioned, container shipping is one of the most harmed business for an international port during the COVID-19 infection, the container service and the port of Shanghai is selected as the case for further economic loss estimation in this research.

4.1. Container throughput volume \((QCT_0)\) projection

The development of container throughput in Shanghai Port for the time period 2012 to 2019 (in 10K TEUs) is shown in Fig. 3, where the quarterly data is used as it can reflect the seasonal features within a year and eliminate some accidental factors compared to monthly data.

The graph in Fig. 3 clearly shows a linear trend with seasonal variations. The seasonal variations exhibit an explicit downward movement at the first quarter of every year. Illustrations demonstrating the smoothness of the sequence are shown in the Appendix.

The Winter’s additive seasonal exponential smoothing model with a linear trend provides an easy way to analyze this time series. The comparison between three seasonal exponential smoothing models (listed in Table 8) is also conducted to verify that the additive method provides the smallest forecasting errors. For the coefficients in Eqs. (17)–(20), when obtaining the values as \(\alpha = 0.555, \beta = 0.002\) and \(\gamma = 0.001\), the time series are fitted best as shown in Fig. 4. The detailed data is listed in Table 9.

With the Winter’s additive seasonal exponential smoothing model, the container throughput volume \((QCT_0)\) projection from 2020 to 2022 is presented in Table 2.

4.2. Scenario setting and QCT projection

Based on the historical data of YoY growth rate of quarterly container throughput, a “V” shape could be observed (as shown in Fig. 5), this indicates there seems to be a sign of recovery from Q2 of 2020 as the declination is shrinking. Based on the actual recovery trend and unanticipated lasting recovery trend, 5 scenarios have been set to depict the potential recovery trend of the port.

The detailed settings of each scenario are listed as below

- **Scenario I**, the V-shaped (normal) recovery scenario: the setting of \(\delta\) follows the trend of the recovery form 2020 Q1 to 2020 Q2 and continues to the end of this V-shaped recovery period: 2020 Q4. Thus, the calculation of \(\delta\) for each quarter follows the same linear trend with the values of \(\delta_{2020 \ Q1} \to \delta_{2020 \ Q2}\).
- **Scenario II**, the W-shaped (normal) recovery scenario: the setting of \(\delta\) follows the same trend of the recovery from 2020 Q1 to Q3 2020 in the V-shaped recovery scenario and then declines in 2020 Q4 and 2021 Q1, then turns to increase linearly to 2021 Q4. For model tractability, the value of \(\delta\) of 2021 Q1 is set as \(\delta_{2021 \ Q1} = -7.0\%\), so, the values of \(\delta\) for other quarters could be obtained.
- **Scenario III**, the L-shaped recovery scenario: the values of \(\delta\) are set to follow a linear growth trend from 2020 Q2 \((\delta_{2020 \ Q2} = -3.6\%)\) to Q4 2022 \((\delta_{2022 \ Q4} = 5.0\%)\) at the end of the L-shaped recovery period.
- **Scenario IV**, the V-shaped (optimistic) recovery scenario: as some ports survive in the beginning of the pandemic, surging shipping demands may help prolong the recovery duration and growth rate. Based on this rationale and the assumptions of Scenario I, instead of hovering at around 5% after the period of recovery, the \(\delta\) continues to rise in the post-epidemic era, following the same linear trend and reaches 65.1% in 2022 Q4.
- **Scenario V**, the W-shaped (optimistic) recovery scenario: as is similar to Scenario IV, based on Scenario II, \(\delta\) continues rising up in 2022 and \(\delta_{2022 \ Q4} = 21.0\%\).

The values settings of each scenario are listed in Table 3.

The detailed estimations of values of \(\delta\) for each quarter under different scenarios are shown in Fig. 6.

4.3. Parameter calibration

The port of Shanghai is selected as the case study in this research as it experienced a sudden decline of shipping business and then recovered gradually. It would be a suitable case which has faced recession and recovery periods for estimating the potential economic losses. The data of containership operations of the port of Shanghai is used for calculation.

For the calculation of Eq. (6), containerships are classified into 4 size segments, that are 0–4000 TEU, 4000–8000 TEU, 8000–12000 TEU and 12000 + TEU in this research. It is assumed that containerships calling the port have the same average size \(U\) within each size segment. Due to data limitation of percentage
Table 3. Scenarios setting details.

| Scenario type | Scenario duration (in quarters) | Sign of the end of recovery |
|---------------|---------------------------------|-----------------------------|
| V-normal      | 4                               | YoY rate (δ) increases to and remains stable at the level of 5% |
| V-optimistic   | 12                              | (Under optimistic scenarios, the trend of increase continues) |
| W-normal      | 8                               |                             |
| W-optimistic   | 12                              |                             |
| L             | 12                              |                             |

4.4. Numerical results

With the parameters, the estimated values of numbers of calling containerships are shown in Fig. 7. During the first two quarters in 2020, the quarterly calling containerships were estimated to decrease by 252 and 112 respectively. In the V-shaped recovery scenario, the number of the containerships calling at the port bounced back acutely and exceeded that of the usual condition, not to mention the V-shaped (optimistic) scenario. In the W-shaped recovery scenario, during 2020 Q4, 2021 Q1, 2021 Q2, and 2021 Q3, the number of calling containerships increased by 240, 368, and 368 respectively.
Q2, 2021 Q4, the quarterly calling containerships were estimated to decrease by 190, 487, 272 and 161 respectively. In the W-shaped (optimistic) recovery scenario, during 2022 Q1 and 2022 Q2, the quarterly calling containerships decreased by 398 and 53 respectively, but a bounce appeared in the second half of the year. In the L-shaped recovery scenario, from 2020 Q3 to 2022 Q4, the downtrend lasts and the average number of decreased ship callings is 219 (82, 190, 360, 203, 153, 241, 398, 137 and 211 respectively) but will be stabilized in the final stages, which is roughly in line with the magnitude of changes in normal operating conditions regardless of the COVID-19 outbreaks.

The estimated economic losses of the container port of Shanghai in each scenario are shown in Fig. 8. It could be seen that as with the shortest recovery period, the V-shaped scenario would experience an economic loss of about 48.9 million CNY. The W-shaped scenario experiences a potential loss of 344.4 million CNY (172.2 million CNY per year) and the L-shaped scenario would experience a loss of 630.8 million CNY (315.3 million CNY per year). It also reveals that although the duration of the recovery process of L-shaped scenario is only 3 times that of the V-shaped scenario, while the economic losses are more than 10 times of the V-shaped scenario. The percentage of the economic losses to the revenues that are estimated regardless of the epidemic outbreak impact (based on N₀) is also shown in the line in Fig. 8.

The results also reveal that the longer duration the recovery lasts, the higher loss the port will suffer. Interesting result shows that under the V-shaped (optimistic) scenario, with the surging recovery and growth, port could obtain a revenue of 2675 million CNY within three years, as a 34.85% revenue increase in the containership business excluding fee rate fluctuations. For the W-shaped (optimistic) scenario, growth in port container throughput from the second half of 2022 onwards compensates for some of the losses during the outbreak, the total potential loss would be shrunk to around 298 million CNY.

The detailed descriptions of sub-losses are shown in Table 7 and Fig. 9. It could be seen that the loss of port due (Lₚₜ), the loss of handling service (Lₕₛ), the loss of berthage charge (Lₚₛ) and the loss of port facility security fee (Lₚₛ) are the major losses among all the sub-losses, which account for about 30%, 26%, 16% and 14% of the total direct losses respectively.

5. Discussion

5.1. Sensitive analysis

The previous sections have estimated the economic losses of a typical container port and results reveal that during the epidemic outbreaks, the port would suffer heavy losses in most
The economic losses of liquid bulk ship and dry bulk ship can be got similarly, which will not be repeated here.

Fig. 8. Total loss and loss percentage. The economic losses of liquid bulk ship and dry bulk ship can be got similarly, which will not be repeated here.

Table 5
Fee rates and other parameters.

| Parameter | Unit       | Value | Remark                                   |
|-----------|------------|-------|------------------------------------------|
| r_{pd}    | CNY/TEU   | 17    | Null                                     |
| r_{fs}    | CNY/TEU   | 8     | Null                                     |
| r_{bu}    | CNY/ship call | 4000 | >3000 net tonnage                        |
| r_{pl}    | CNY/ton   | 0.45  | 40001–80000 net tons part               |
| r_{pl}  | CNY/ton   | 0.375 | 80000–120000 net tons part             |
| r_{bu}  | CNY/ship call | 4000 | 150–180 m                                |
| r_{pl}  | CNY/ship call | 10000 | 275–300 m                               |
| r_{pl}  | CNY/ship call | 11000 | 325–350 m                               |
| r_{pl}  | CNY/ship call | 11500 | 350–390 m                               |
| r_{pl}  | CNY/ton/day | 0.25  | /                                        |
| r_{pl}  | CNY/TEU   | 9     | /                                        |
| T_{b}     | day       | 6     | /                                        |
| If       | /         | 85%   | /                                        |

*If the pilotage distance is 10 nautical miles or less, and the vessel is 120,000 net tons or less, the pilotage fee will be charged according to the rates specified in the table. If the pilotage distance is 10 nautical miles or less, and the pilotage fee is over 120,000 net tons, the pilotage fee will be 49,000 CNY. The average ton is 150,000 tons for these ships, meaning the pilotage fee rate for the ships larger than 12,000 TEU can be seen as 0.327 CNY/ton (without segmentation).*

Source: The rates are referred from the Ministry of Transport of the People’s Republic of China (http://www.mot.gov.cn/); the value of parameter If is sourced from Shanghai Shipping Exchange (https://www.sse.net.cn/datacenter).

Table 6
Some parameters of the virtual sample vessel and related fee rates.

| Parameter | Unit | Value |
|-----------|------|-------|
| Ship size (U) | TEU | 5196 |
| Ship size (U) considering loading factor | TEU | 4416 |
| Net tonnage (W) | ton | 44160 |
| r_{pl} | CN/ton | 0.4026 |
| r_{pl} | CNY/ship call | 9176 |
| r_{pl} | CNY/ton | 0.0426 |
| r_{pl} | CNY/ship call | 9176 |

*According to Leonardi and Browne (2010), 1 TEU is estimated to weight as 10 tons.

Table 7
Value of different sub-losses (mil. CNY).

| BAU | V-shaped | W-shaped | L-shaped | V-shaped (optimistic) | W-shaped (optimistic) |
|-----|----------|----------|----------|----------------------|----------------------|
| l_{pd} | 0  | 14.858 | 104.530 | 191.454 | 191.454 | 811.918 | 90.331 |
| l_{fs} | 0  | 13.110 | 92.233 | 168.930 | 168.930 | 716.399 | 79.704 |
| l_{bu} | 0  | 7.866  | 55.340 | 101.358 | 101.358 | 429.839 | 47.822 |
| l_{pl} | 0  | 6.992  | 49.191 | 90.096  | 90.096  | 382.079 | 42.509 |
| l_{to} | 0  | 4.384  | 27.144 | 49.660  | 49.660  | 192.281 | 21.393 |
| l_{bw} | 0  | 1.816  | 12.777 | 23.401  | 23.401  | 99.240  | 11.041 |
| l_{bs} | 0  | 0.792  | 5.570  | 10.201  | 10.201  | 43.261  | 4.813  |
| l_{bd} | 0  | 48.954 | 344.395| 630.782 | 630.782 | 2675.018| 297.614 |
cases but may also gain revenue under extreme recovery environment. While according to Linton Nightingale (2020), unlike port operators usually have few managerial tools to mitigate economic losses due to such a sudden external epidemic outbreak that induced a sharp decline in the number of calling containerhips. Shipping companies may alter operational strategies such as control or maintain service routes or implement blank flights to meet the dynamic equilibrium between demand and supply. While for the side of port, operators cannot seal the berths or adjust processing capabilities for a certain period. Moreover, port operators usually have their own annual contract prices and are unlikely to increase prices during economic downturns, so their revenues will be hit hard.

Thus, it is crucial for the port operators to cut costs during the epidemic outbreaks. The following parts will examine how the berthing time ($T_b$) and the calling ships' fleet structure affect the overall economic losses of the port.

### 5.1. Berthing time ($T_b$)

During the epidemic outbreak, most ports, including the port of Shanghai, due to changes in call procedures (such as sanitary inspections, staff alienation, port or related service interruption, the need to maintain a safe distance and clean equipment), have experienced longer shift time. Besides, the efficiency of container handling has been reduced significantly due to the limitation of operational staff under the self-distancing and blockage policies during the initial phase of the outbreak, leading to a backlog of queues of ships in the port. When the number of ships is larger than the number of berths, the average berthing time of each ship would also increase. The longer the berthing time, the lower the loading and unloading efficiency, which means the lower the service level, then the number of ships coming to call will also decrease. For a single containerhip, the berthing time ($T_b$) of ships has become longer due to the low efficiency, but for the whole port, when the total number of calling ships have decreased, the number of ships served per berth per unit time will decrease. Finally, fewer ships and fewer container throughput leads to the reduction of berthing charge.

As $T_b$ is a key factor which affects the revenue of berthing service, the variance of $T_b$ might be crucial for the overall port's economic losses. Take the V-shaped recovery scenario as an example, the sensitivity analysis of $T_b$ is conducted. The results are shown in Fig. 11. It shows that the berthing charge loss decreases with the decline of the berthing time $T_b$, that is, improving handling efficiency at berth helps reduce losses and control risk levels (see Fig. 10).

For instance, assuming that the $T_b$ drops by 50%, the total loss can decrease by about 13.39% on the basis of 48.9 million CNY (as listed in Fig. 8). This indicates that even during epidemic outbreaks, ports could reduce certain losses by improving handling efficiency.

### 5.1.2. Fleet structure

From the perspective of shipping companies, they may adjust their fleet structure to mitigate the risks brought by the COVID-19 outbreak, such as deploying more small-size containerhips for higher loading rate, better utilization and higher agility. As different vessel size segments account for different levels of oil containment boom usage fee, pilotage fee and towage fee, so the adjustment of fleet size may impact the revenue and loss structures of ports seriously.

In this section, a sensitivity analysis of port’s loss on calling fleet structure is conducted, the results are shown in Fig. 12, where the percentage of number of vessels of each size segmentation are variables as the x, y, z coordinates, the volume of economic losses are depicted as the sizes of the bubbles. The results reveal that when the proportion of large ships (larger than 8000 TEU) increases, the sum of losses of oil containment boom usage fee, pilotage fee and towage fee become smaller and vice versa. This indicates that when a container port is more capable of serving larger containerhips, the port will suffer less economic losses under the epidemic outbreaks.

### 5.2. Policy and managerial implications

This article hints at the importance of quantifying the economic losses of the port under different operational recovery scenarios. The economic losses under three recovery scenarios are estimated and results indicate that container ports will suffer certain economic losses no matter what kind of recovery scenario is. Besides, the slower the economy is ready to recovery, the more economic losses the port will suffer. As ports are important nodes for global trade and economic development, the recovery subsidies for ports should be considered by policy makers to sustain the short to midterm normal operations of ports.

As for the ports, the results show that improved handling efficiency and accommodating larger containerships could help to reduce losses. In the short run, the ports should take actions to improve the handling efficiency by better utilizing the workers under quarantine policies. For the mid to long run, ports should invest more on intelligent infrastructure to improve the handling efficiency and enlarge their capability of serving larger ships. Because when during the epidemic outbreaks such as COVID-19, quarantine policies may restrict personnel from working at physical sites, thus automatic handling regardless of infection is crucial for ports' operations in the future.

### 6. Conclusion

This article focuses on identifying the impacts of COVID-19 on the seaport by estimating the economic losses. The key problems of establishing economic loss estimation framework, estimating port service volume, setting of port recovery scenarios have been addressed. The key conclusions of this research are drawn as follow:

- Three basic recovery scenarios (V, W, L-shaped) have been established to estimate the economic losses of container
ports. Based on the assumptions, the economic losses of the port of Shanghai under V-shaped scenario is about 48.9 million CNY, under W-shaped scenario is about 344.4 million CNY and under the L-shaped scenario is about 630.8 million CNY.

- The slower the shipping and port recovers (from V to L scenario), the larger economic losses the port would suffer. Besides, the loss of port due ($L_{pd}$), the loss of handling service ($L_{hs}$), the loss of port facility security fee ($L_{fs}$) and the loss of berthage charge ($L_{bc}$) are the major losses among all the sub-losses.
- Two additional scenarios (optimistic V, W-shaped optimistic) charactering persistent recovery have been proposed to estimate the port’s performance considering the situation of surging growth of demand in the post epidemic era. Under the optimistic V-shaped scenario, the port would gain a net revenue about 2675.0 million CNY due to the surging growth of demand. Under the optimistic W-shaped recovery, the loss will be compensated from 2022 Q3 and the overall economic losses will be shrunk to be about 297.6 million CNY.
- Port handling efficiency and ships’ fleet structure are crucial for reducing economic losses of the port. Improved container handling efficiency would reduce the overall berthage time ($T_{b}$) and then reduce port’s economic loss. Besides, accommodating larger containerships would help reducing economic losses.
- Suggestions for policy makers on subsidizing ports during epidemic outbreaks and port operators on strengthening intelligent infrastructure investment in the future have been made.
Table 8
Comparison of three kinds of seasonal exponential smoothing model.

| Model              | Number of predictors | Model fit statistics | Ljung–Box Q(18) | Number of outliers |
|--------------------|----------------------|----------------------|------------------|-------------------|
|                    |                      | Stationary R-squared | R-squared | Normalized BIC |
| Simple seasonal    | 0                    | 0.362                | 0.956           | 6.355             | 10.022 | 16 | 0.865 | 0 |
| Winter's additive  | 0                    | 0.583                | 0.970           | 6.103             | 9.657  | 15 | 0.841 | 0 |
| Winter's multiplicative | 0              | 0.524                | 0.967           | 6.189             | 7.472  | 15 | 0.943 | 0 |

Fig. 13. Difference of the time series of quarterly container throughput volume.

CRediT authorship contribution statement

Xiaoxuan Zhou: Writing – original draft, Review. Lei Dai: Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. Danyue Jing: Methodology, Writing – original draft. Hao Hu: Writing – review & editing. Yubing Wang: Writing – original draft, Review.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See Fig. 13, Tables 8 and 9.

Table 9
Exponential smoothing model parameters.

| Exponential smoothing model parameters | Estimate | SE | t | Sig. |
|---------------------------------------|----------|----|---|------|
| Alpha (Level)                         | 0.555    | 0.202 | 2.748 | 0.010 |
| Beta (Trend)                          | 0.002    | 0.025 | 0.085 | 0.933 |
| Gamma (Season)                        | 0.001    | 0.139 | 0.007 | 0.994 |

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