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Port resilience in the post-COVID-19 era

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ABSTRACT

With the COVID-19 pandemic evitably becoming the "New Normality" and will continue to impact human society much longer than anticipated, it is essential to explore effective measures that global ports can take to adapt to unexpected challenges in the post-COVID-19 era. This paper builds a port resilience index system based on the entropy weight method from a multistakeholder's view. We utilize the port resilience index system for 22 major Chinese ports during 2020–2021. We further investigate the direct impact of port resilience on port governance performance. Our results indicate that resiliently-governed ports can guarantee higher port throughput while sustaining lower congestion when facing challenges from the global pandemic.

1. Introduction

The COVID-19 pandemic has lasted for more than three years and generated enormous impacts on the worldwide economy. Especially in global maritime trade, the COVID-19 pandemic has been estimated to result in a 3.8% decrease in 2020 (United Nations Conference on Trade and Development [UNCTAD], 2021). Moreover, it is evaluated that the COVID-19 pandemic will continue to impact human society for much longer than it was initially anticipated (Shrestha et al., 2020). Therefore, recent literature suggests considering global transportation, especially port governance, in the context of "the New Normality" of the worldwide pandemic, that is, exploring the adaptive port governance in the post-COVID-19 era (Notteboom and Haralambides, 2020). Specifically, how to govern a resilient port system that guarantees normal port operations even facing unexpected global pandemic challenges becomes the essential question that all major ports should take into consideration.

Prior literature has suggested using port resilience to represent ports' systematic capability to adjust to a new state of normality after a disruption (Chopra and Sodhi, 2004; Notteboom et al., 2021; Verschuur et al., 2020). Especially as a complex adaptive system, a resilient port is more capable of adapting to unexpected emergency events (UEEs). These previous studies mainly examine the concept of port resilience in the context of climate change, while other severe challenges that global ports are increasingly facing, notably the global pandemic, are underexplored in port resilience research. Furthermore, as it is consent that resilience is a system concept, establishing a comparable, cross-port resilience system in a generalized framework helps to extend the robustness and external validity of current port resilience research (Li et al., 2022).

Therefore, in this paper, we first establish a generalizable port resilience index system based on the entropy weight method (EWM), integrating the port, the hinterland, and the local government as significant stakeholders in port operations. We then take China as our research context and calculate the port resilience index for the 22 largest Chinese ports monthly during 2020–2021. Subsequently, we investigate the direct effect of the port resilience index on port throughput and congestion, two of the most essential port governance performance indicators. Our results suggest that resilient-governed ports sustain higher cargo throughput while enjoying fewer port congestion issues even facing the threats of COVID-19. In addition, considering the unique feature of the Chinese context, we further extend our analyses to explore alternative port resilience index before COVID-19 to reflect port operations considering other threats rather than the pandemic.

The rest of the paper is organized as follows. Section 2 reviews relevant literature, presents the research background, and figures out the literature gap. Following that, Section 3 illustrates the data sources and research methodology. Next, Section 4 reports empirical analysis, robustness tests, and additional analyses comparing the port resilience before and after COVID-19. Finally, the results, contributions, and future research directions are discussed and concluded in Sections 5.

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2. Literature review

2.1. Resilience

"Resilience", proposed with a focus on coping with abnormal situations (Holling, 1973; Klibi et al., 2010; Timmerman, 1981), is increasingly emphasized across multiple domains, especially facing the challenge from the recent epidemic. Prior literature defines resilience as the ability of a system to resist and recover from, and adapt to adverse events/shocks (Linkov et al., 2014). The focus of resilience is to sustain performance or even achieve a more desired outcome through coping with changes (Christopher and Rutherford, 2004).

As a concept first developed in the field of ecology, resilience was initially used to describe the capacity/capability of an ecology system to absorb external disturbances while maintaining its healthy state. Therefore, resilience is a system concept, and has been widely adopted in various fields, such as transportation systems, economic systems, social and community systems, and organizational management. Prior literature also indicates that resilience has two dimensions, one is inherent (or sometimes called mitigation resilience, see (Naderpajouh et al., 2018), and the other is adaptive resilience (Panahi et al., 2022). Mitigation resilience is the ability of a system to prevent or reduce the risk of unexpected changes. In contrast, adaptive resilience is stated as the ability to adapt to changes through proactive measures and procedures (León-Mateos et al., 2021). Recent studies have stressed adaptive resilience, for it represents efforts that a system could proactively take to reduce the vulnerability to unexpected changes.

Prior literature has suggested three ways to model and measure resilience. The first approach measures the resilience of a system based on the sum of the resilient performance of each actor in the system. Specifically, the first approach adopts the weighted sum of each node's calculated resilience as the entire network's resilience. However, this approach is challenged for being inherently a reflection of the given reliability value of individual nodes while failing to capture the system nature of the concept of resilience (Christopher and Rutherford, 2004).

Therefore, a recent literature stream emerges to call for adopting a stochastic mixed-integer program to consider the resilience in the entire system to differentiate resilience from the concept of reliability. Furthermore, this approach suggests that considering the systematic metaphor, the resilience of a system should be measured using a mathematical aggregation of a set of indicators (Verschuur et al., 2022).

The third approach similarly also suggests adopting a composite index to measure resilience. This approach suggests that resilience cannot be measured directly as a systematic construct but should be operationalized to a set of observable variables (Markolf et al., 2019).

2.2. Port resilience in response to unexpected emergency events

Notably, in the field of port governance, previous studies have noticed that ports are increasingly facing a variety of threats to their long-term survival, governance, and growth. Therefore, "resilience" has been extensively adopted to present ports' governance and capabilities to adapt to changing environments (Becker and Caldwell, 2015; Zhou et al., 2021). Ports are suggested be viewed as complex adaptive systems (CASs), with port resilience as the port's capability to adjust to a new state of normality after a disruption (Chopra and Sodhi, 2004; Notteboom et al., 2021; Verschuur et al., 2020).

To examine port resilience in response to unexpected emergency event (UEEs), prior literature either develops scenario settings to identify port resilience features (e.g., Panahi et al., 2022), or develops a composite index system for one specific port. For instance, Hein et al. (2022) propose that port resilience is a composite index including five dimensions: natural environment, society, built environment, port governance, and risks the port faces. Becker and Caldwell (2015) suggests six dimensions of port resilience: social, community capacity, economical, institutional, infrastructure, and hazard. However, most of the previous studies only examine port resilience in adapting to climate change while neglecting challenges from other UEEs. Actually, in addition to climate change, the sustaining global epidemic has proven to present more abnormal changes/hazards to port governance. As the global epidemic, COVID-19 has lasted for more than three years and is becoming the new normality. The influence of COVID-19 on the global supply chain, especially on global sea port governance, is ever long-lasting than it was initially expected to be (Notteboom and Haralambides, 2020; Verschuur et al., 2021). Therefore, the concept of "port resilience" is also changing to reflect challenges from unexpected disasters, especially the global pandemic that ports are facing.

2.3. Research background: port resilience before and after the COVID-19 era

Based on the literature review in sections 2.1 and 2.2, it is clear that before the COVID-19 era, port resilience literature mainly considers the port's capability to adjust to a new state of normality after a disruption caused by UEEs, mainly from extreme weather. However, it is suggested that other UEEs, in addition to climate change, should be considered when constructing the port resilience index to fully reflect the threats ports face in the real world. Especially under the current global pandemic background, the recent literature calls for examining port resilience especially in terms of facing the global pandemic (Notteboom and Haralambides, 2020; Verschuur et al., 2021), that is, exploring what a resilient port in the post-COVID-19 era is?

The novel Coronavirus (SARS-CoV-2), which was first reported in December 2019, and rapidly spread to the worldwide pandemic, was officially named "coronavirus disease 2019" (COVID-19) by the World Health Organization (WHO) (Guan et al., 2020). The global pandemic outbreak has severely impacted global trade and supply chains. Studies have shown that since the outbreak, global trade has declined significantly, with the increasing shortage of supply (Gruszczynski, 2020; Verschuur et al., 2021). Especially in terms of global ports, one key element in global supply chains, the pandemic has resulted in a significant reduction in port throughput worldwide. According to statistics, container vessel throughput at major global ports decreased by 20%–50% in the second quarter of 2020 (Sea-Intelligence. 2020).

In addition to port throughput, the global pandemic also has intensified the uncertainty in container port supply chains and logistics systems (Michail and Melas, 2020; Russell et al., 2022), therefore causing the closure of shipping lines, and disrupting global transportation system (Xu et al., 2021). What is more, the global pandemic has intensified port congestion. According to the Sea-Intelligence, in July 2021, the average delay time continued increasing from June's 6.53 days to July's 6.88 days. The average waiting time for ships at the Port of Los Angeles increased to 8.5 days from 7.6 days at the end of August, due to the strict quarantine policy and city lockdowns (Koyuncu et al., 2021). One reason is that the port lacks the experience and capabilities to deal with these unexpected challenges, while another reason is that the port is experiencing a shortage of labor supply, which simultaneously severely decreases the port operation efficiency and effectiveness (Cullinane and Haralambides, 2021; Guerrero et al., 2022).

However, the noteworthy point is that Chinese ports perform differently from ports from the rest of the world. Fig. 1 presents major Chinese ports' domestic trade cargo throughput (DTCT) and foreign trade cargo throughput (FTCT) during 2019–2021. As is shown in Fig. 1, both these two dimensions of cargo throughput remained relatively high even facing the challenge of the global pandemic.[1] Fig. 2 presents the congestion trend of major Chinese ports during 2019–2021. As is shown in Fig. 2, the average hours of vessels waiting at the port (AWT) and the average number of container ships waiting at the port (SWP) witnessed

[1] The sharp decrease in DTCT and FTCT in February 2019, 2020, and 2021 is due to the Chinese New Year.

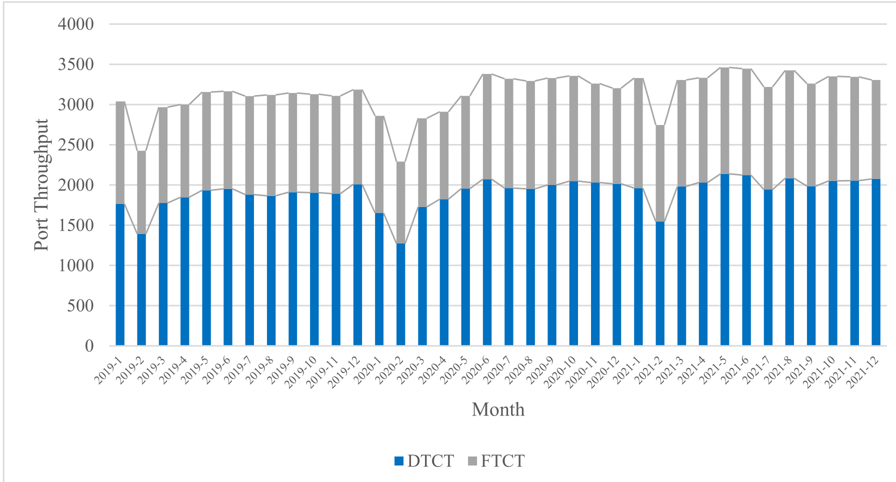

Fig. 1. Port throughput of Chinese major ports before and after COVID-19

[2] Source: the Ministry of Transport of the People's Republic of China (MOT, https://www.mot.gov.cn/).

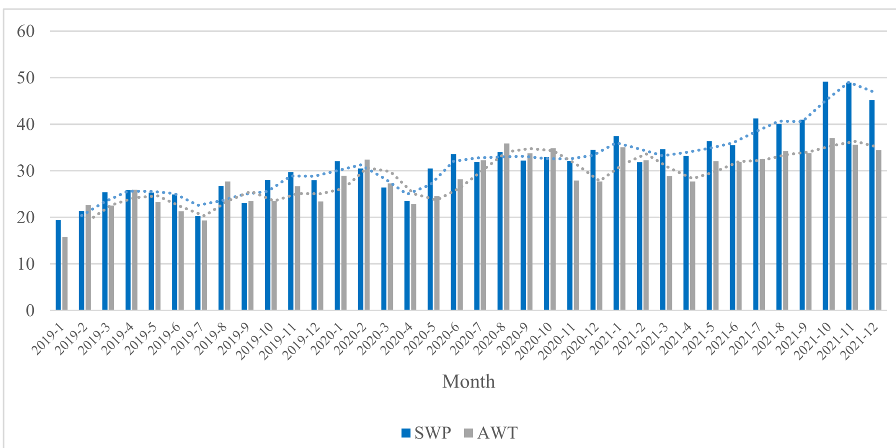

Fig. 2. Port congestion of Chinese major ports before and after COVID-19[3]

[3] Source: Vessel Value Visualization (https://port.myvessel.cn).

an increasing trend during the global pandemic, meaning the port congestion was worsened. During the most severe COVID-19 outbreak waves, on average, containers must wait for almost 35 h at the port to berth. Meanwhile, there are around 50 containers that need to wait at the port to berth. However, usually, after three months of each pandemic wave, both the AWT and SWP decreased, suggesting that the port congestion will be relieved to some extent. One explanation for Chinese ports' more robust performance is the Chinese government's unique, stringent, agile pandemic control policies and practices. It is suggested that the effective epidemic prevention and control policies adopted by the local governments have played a positive role in port governance during the pandemic.

2.4. Literature gap: Port resilience and port governance performance

Based on the above literature review, we identify several literature gaps that this paper aims to fill. First, although prior literature has proposed different measures of resilience, the concept of "port resilience" is relatively new. Only a limited number of studies have noticed the importance of resilience for ports to sustain their operations. However, these studies mainly focus on the port resilience to climate change (e.g., León-Mateos et al., 2021), while neglecting other aspects. A recent literature stream is calling for examining port resilience to other unexpected extreme events, especially to the global pandemic (Cullinane and Haralambides, 2021; Panahi et al., 2022). Meanwhile, with the global pandemic is becoming the "new normality", how to build a resilient port system in the post-COVID-19 era emerges as an essential issue (Notteboom and Haralambides, 2020). Still, although it is more widely accepted that resilience should be measured as a system concept, previous port resilience research either uses expert interviews to identify port resilience features (e.g., Panahi et al., 2022), or only develops a composite index system for a single port (e.g., Becker and Caldwell, 2015). A more general post resilience measurement established from a systematic view of multiple stakeholders, which can be adopted to compare different ports is in need.

Second, as pointed out in the above section of the literature review, a minimal empirical examination is available about port resilience on port performance in real-world situations. Although it is increasingly noticed the importance of port resilience, the direct impact of port resilience stays underexplored. Especially, in the post-COVID-19 era, what will a resilient system brings to ports? This paper aims to answer this question in an empirical way.

3. Methodology

3.1. Sample

We use China as our research context in this study for several reasons. First, according to the World Shipping Council ("Top 50 Ports," 2022), Chinese ports account for more than half of the top 50 global container ports based on throughput volume. So focusing on Chinese ports is representative of the largest global ports. Second, China is a large economy. Even within China, port governance practices are diverse. Thus, using Chinese ports as our research sample could guarantee enough variety between each port without loss of generality. Last but not least, considering the heterogeneity of government response to COVID-19 across different countries (China has a unique pandemic control and prevention system), it is unreasonable to make a cross-country comparison in evaluating port resilience facing the pandemic. Therefore, in this study, we select the 22 largest Chinese ports based on their throughput volume. The complete ports list (with port resilience index ranking) is shown in Table 2.

3.2. Port resilience index system in the post-COVID-19 era

To build a complete port resilience index system, it is suggested to consider multi-stakeholders' points of view. In this paper, following prior literature, we take the port, the hinterland, and the local government as major stakeholders in sustaining port resilience.

First, from the port's viewpoint, we choose three indicators to reflect the port's resilience in the post-COVID-19 era. Specifically, we adopt port governance efficiency and whether the port is a smart port and a national logistics hub to represent the port resilience from the port's view. Prior literature has pointed out the critical role of port governance efficiency in global port governance (Brooks and Pallis, 2008; Ha et al., 2019). The average berth occupancy rate measures the port governance efficiency, that is, the ratio of time the berth is occupied by a vessel to the total time available in that period.

Meanwhile, in the post-COVID-19 era, the recent literature stream points out the importance of automation and digitalization to port resilience. Innovative digital technologies, such as Artificial Intelligence (AI), big data, Internet of Things (IoT), 5G, and cloud computing, are transforming the industry of ports and container shipping to be more connected and "smart". Furthermore, it is suggested that with the changing demands of global trade, ports face geopolitical issues and intense challenges. Thus, it is even more paramount today for ports to coevolve with changes and become "smart" (Molavi et al., 2020; Yau et al., 2020). Therefore, we adopted whether the port is evaluated as a "smart" port according to the official report released by the Ministry of Transport of the People's Republic of China.

In addition, prior literature suggests that a bigger port with more connection with the transportation system usually possesses stronger resilience facing unexpected challenges. Especially being the logistics hub enables the port to integrate its surrounding transportation facilities, such as airline terminals, railways, and highways, to optimize its logistics efficiency (Chen et al., 2018; Russell et al., 2022). Therefore, according to the official report released by the National Development and Reform Commission of the People's Republic of China, we adopted whether the port is recognized as a national logistics hub.

Second, prior literature also suggests considering the hinterland as an essential stakeholder in examining port resilience. Specifically, we adopt the ICT infrastructure and digital industrial convergence to represent the port resilience from the hinterlands' viewpoint. It is suggested that the information infrastructure of the hinterland supports the port with strong digital services, thus enabling the port to resist unexpected challenges (Kia et al., 2000; Zhou et al., 2021). Therefore, we adopted the ICT infrastructure of the local city where the port is located, according to the official report released by the Annual Statistics Yearbook.

In addition, digital industrial convergence reflects the contribution of digital industries to economic growth. Prior literature has noticed the importance of the industrialization of digital, electronic, software/hardware, and information service industries of the local economy to support the health governance of the port (Becker and Caldwell, 2015; Chen et al., 2017). Meanwhile, it is also suggested that the digitalization transformation of traditional industries enables the port to better integrate with the local transportation system. Therefore, according to the official report released by the White Paper on China's Urban Digitalization Evolution Index, we adopted the digital industrial convergence level of the local city where the port is located.

Third, the local government is also critical in determining port resilience. Prior literature suggests that a responsive local government is also decisive in building a resilient port system (Guerrero et al., 2022; March et al., 2021; Verschuur et al., 2022). Specifically, we adopt the local government's response to the pandemic and governance score to represent the port's resilience from the local government's view. How well the local government responds to the pandemic determines how severely the pandemic affect the port operations. Therefore, we adopted the local government response to COVID-19, indexed by the Oxford COVID-19 Government Response Tracker (OXCGRT) database.

In addition, prior literature also states that local governance reflects the capability of the local government to sustain the whole society, even facing unexpected events (Girard, 2010; Hein et al., 2022; Komugabe-Dixson et al., 2019). Therefore, according to the official report released by the White Paper on China's Urban Digitalization Evolution Index, we adopted the local governance score of the city where the port is located. The local governance score is a comprehensive index, including how well the local government performs in terms of education, medical care, transportation, social insurance, poverty alleviation, the business environment, and the living environment. We then integrate all of the above indicators to build the port resilience index. The detailed summary of each indicator is presented in Table 1.

3.3. Measurement

3.3.1. Independent variable: Port resilience index

Port Resilience Index (PRI): To calculate the PRI in a systematic manner, we used the entropy weight method (EWM) to alleviate the influence of different measurements and magnitude of various indicators of the PRI. Specifically, we followed the four stages.

At stage one, we first standardized the original value for each indicator, using the following equation:

$$y_{ijt} = \frac{x_{ijt} - \min(x_{ijt})}{\max(x_{ijt}) - \min(x_{ijt})}, i = 1, 2, \ldots\ldots, m;\ j = 1, 2, \ldots\ldots, n; t = 1, 2, \ldots\ldots, l \tag{1}$$

Where x_{ijt} is the jth index's value in the ith port at time t. All indicators in our measurement are positive direction variables, meaning the bigger the better.

At stage two, we calculated the entropy for each index using the following equations:

$$p_{ijt} = \frac{y_{ijt}}{\sum_{i=1}^{m} y_{ijt}}, i = 1, 2, \ldots\ldots, m;\ j = 1, 2, \ldots\ldots, n; t = 1, 2, \ldots\ldots, l \tag{2}$$

$$E_{jt} = -\frac{1}{lnm} \sum_{i=1}^{m} p_{ijt} \ln(p_{ijt}),\ i = 1, 2, \ldots\ldots, m;\ j = 1, 2, \ldots\ldots, n; t = 1, 2, \ldots\ldots, l \tag{3}$$

Where E_{jt} is the entropy of the jth index at time t

At stage three, we calculated the weight for each index using the following equations:

$$g_{jt} = 1 - E_{jt}, j = 1, 2, \ldots\ldots, n; t = 1, 2, \ldots\ldots, l \tag{4}$$

Table 1
Port resilience index during the COVID-19.

Indicator	Stakeholder	References	Data source	Distribution
Port governance efficiency	Port	(Brooks and Pallis, 2008; Ha et al., 2019)	Vessel Value Visualization[a]	mean = 0.48, S.D. = 0.23
Smart port	Port	(Molavi et al., 2020; Yau et al., 2020)	The Ministry of Transport of the People's Republic of China[b]	1 = smart port; 0 = otherwise; mean = 0.78, S.D. = 0.41
National logistics hub	Port	(Chen et al., 2018; Russell et al., 2022)	The National Development and Reform Commission of the People's Republic of China[c]	1 = national logistics hub; 0 = otherwise; mean = 0.32, S.D. = 0.47
ICT infrastructure	Hinterland	(Kia et al., 2000; Zhou et al., 2021)	Annual Statistics Yearbook	mean = 71.46, S.D. = 13.02
Digital industrial convergence	Hinterland	(Becker and Caldwell, 2015; Chen et al., 2017)	White Paper on China's Urban Digitalization Evolution Index[d]	mean = 61.12, S.D. = 16.11
Government response to COVID-19 index	Government	(Guerrero et al., 2022; March et al., 2021; Verschuur et al., 2022)	Oxford COVID-19 Government Response Tracker (OXCGRT) database[e]	mean = 54.70, S.D. = 11.38
Local governance score	Government	(Girard, 2010; Hein et al., 2022; Komugabe-Dixson et al., 2019)	White Paper on China's Urban Digitalization Evolution Index[f]	mean = 68.57, S.D. = 15.97

[a] https://port.myvessel.cn/.
[b] https://xxgk.mot.gov.cn/2020/jigou/syj/202006/t20200623_3313889.html.
[c] https://www.ndrc.gov.cn/fggz/jjmy/ltyfz/202010/t20201028_1249139_ext.html.
[d] http://deindex.h3c.com/2022/Release/.
[e] https://covidtracker.bsg.ox.ac.uk/
[f] http://deindex.h3c.com/2022/Release/.

Table 2
The detailed port ranking in the port resilience index during 2020–2021.

Ports	PRI in 2020	PRI ranking in 2020	PRI in 2021	PRI ranking in 2021	Upward trend
Guangzhou	0.909892595	1	0.913691448	1	
Nanjing	0.856994359	2	0.888384534	2	
Tianjin	0.851688924	3	0.856684157	4	
Ningbo-zhoushan	0.844644101	4	0.862847763	3	✓
Qingdao	0.824473168	5	0.842082199	5	
Chongqing	0.630667399	6	0.643762962	9	
Xiamen	0.589933399	7	0.716474207	8	
Shanghai	0.588275926	8	0.589236248	10	
Dalian	0.519995431	9	0.794785691	6	✓
Nantong	0.477815415	10	0.489274001	12	
Zhenjiang	0.472092043	11	0.483276614	14	
Jingtang	0.469125208	12	0.783767566	7	✓
Taizhou	0.461720178	13	0.481304863	15	
Huanghua	0.402359475	14	0.419507793	16	
Qinhuangdao	0.40156841	15	0.418674013	17	
Shenzhen	0.337609604	16	0.376683047	18	
Fuzhou	0.267034076	17	0.486464013	13	✓
Dongguan	0.260945091	18	0.267309253	20	
Yantai	0.235215881	19	0.267728751	19	
Beihai	0.213617817	20	0.521311201	11	✓
Zhanjiang	0.185872313	21	0.197611881	21	
Jiujiang	0.17092364	22	0.180260308	22	

$$w_{jt} = \frac{g_{jt}}{\sum_{j=1}^{n} g_{jt}}, j = 1, 2, \ldots\ldots, n; t = 1, 2, \ldots\ldots, l \tag{5}$$

Where w_{jt} is the weight of the jth index at time t

At stage four, we calculated the port resilience index for each port i at time t using the following equation

$$PRI_{it} = \sum_{j=1}^{m} w_{jt} * y_{ijt}, i = 1, 2, \ldots\ldots, m;\ j = 1, 2, \ldots\ldots, n; t = 1, 2, \ldots\ldots, l \tag{6}$$

Where PRI_{it} is the port resilience index of port i at time t, ranging between 0 and 1.

We presented the average trend of the port resilience index in Fig. 3. Fig. 3 shows that on average, Chinese ports experienced an upward trend in their resilience index. We also reported the detailed PRI score and ranking for each port in 2020 and 2021 in Table 2. Table 2 indicates that while the majority of ports stay consistent in PRI rankings, there are five ports improved their port resilience in 2021, witnessing an upward trend in PRI ranking. These ports are Ningbo-zhoushan, Dalian, Jingtang, Fuzhou, and Beihai.

3.3.2. Dependent variable: Port governance performance

Port Throughput: The port throughput is usually measured in two aspects: the domestic trade cargo throughput (DTCT) and the foreign trade cargo throughput (FTCT). DTCT is the total cargo throughput for domestic trade in billion tons, reflecting the total import volume of goods to China. while FTCT is the total cargo throughput for foreign trade, reflecting the total export volume of goods from China. Both of DTCT and FTCT are important measures of port throughput and have been widely adopted in prior studies (Ziran et al., 2022). The port throughput data is obtained from *the Ministry of Transport of the People's Republic of China* (MOT, https://www.mot.gov.cn/).

Port Congestion: Prior literature states that with high vessel traffic volume, ports facing a lack of available labor and operational uncertainty have to make vessels wait for available berths and labor (Kia et al., 2000; Murty et al., 2005). Thus, prior literature widely uses the average vessel waiting time (AWT) for a berth to measure the degree of port congestion (Notteboom, 2006; Talley, 2006a). Meanwhile, prior studies (Talley, 2006b; Yeo et al., 2007) also use the number of container ships that have already arrived at the port but need to wait to dock as another measure of port congestion, that is, ships waiting at the port (SWP). Both of the AWT and SWP are adopted through the website of *Vessel Value*

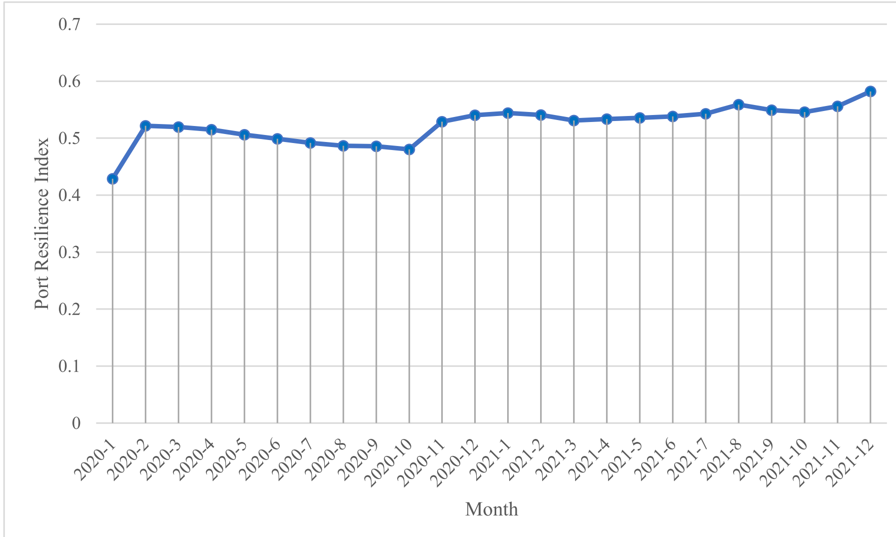

Fig. 3. Port resilience index over 2020–2021.

Visualization (https://port.myvessel.cn/), developed by *COSCO Shipping Technology Co., LTD.* The port congestion data is calculated based on global shipping location information. *Vessel Value Visualization* provides users with real-time port congestion information, and is increasingly acknowledged and adopted by the shipping industry and the academia.

3.3.3. Control variables

New Confirmed Cases (NCC): NCC is monthly new confirmed COVID-19 cases in the province where the port is located. NCC is widely adopted to measure the severity of the COVID-19 pandemic. NCC is extracted from *OxCGRT* database and the National Health Commission.

Gross Domestic Product (GDP): GDP reflects the development of the local economy where the port is located. GDP is obtained from *the National Bureau of Statistics of China* (http://www.stats.gov.cn), and is log transformed.

Consumer Price Index (CPI): CPI is a macroeconomic indicator reflecting the average price change of goods and services purchased by households, and is widely adopted to measure the economic development (Xu et al., 2021). CPI is obtained from *the National Bureau of Statistics of China* (http://www.stats.gov.cn).

Manufacturing Value Added (MVA): MVA is the total estimate of net-output of the local manufacturing activity units of the city where the port is located. MVA is obtained from *the National Bureau of Statistics of China* (http://www.stats.gov.cn)

Population Density (PD): PD is measured by the average number of individuals per square meter in the local city where the port is located. PD is obtained from *the National Bureau of Statistics of China* (http://www.stats.gov.cn), and is log transformed.

3.4. Examination statistic models

To investigate the impact of epidemic control measures on port throughput, we employ a two-way fixed effects model, estimated as below:

$$Port\ Throughput_{it} = \beta_0 + \beta_1 Port\ Resilience\ Index_{i,t-1} + \beta_2 X_{i,t-1} + \beta_3 Port\ Throughput_{i,2019} + \gamma_i + \mu_t + \varepsilon_{it} \quad (7)$$

Where *Port Throughput*$_{it}$ is port domestic and foreign throughput of port i in month t, *Port Resilience Index*$_{i,t-1}$ is the resilience index of the port i, lagged by one month. $X_{i,t-1}$ represents for a vector of control variables of port i, lagged by one month. Prior literature suggests that port performance, especially port throughput could be path dependent and persistent over time. Therefore, it is suggested that the lagged port throughput at the same time of normal year should also be included as repressors to make regression models be "dynamic" in nature, considering the persistent influence of past performance. Thus, we also included the value of the dependent variable at the same month of 2019 as a repressor in the regression models, as suggested by prior studies. γ_i is port fixed effects, controls for the unobserved time-invariant features which constant at each port. μ_t is month fixed effects, controls for the unobserved time-variant features, ε_{it} is the idiosyncratic error term.

To investigate the impact of epidemic cooperation measures on port congestion, we employ a two-way fixed effects model, estimated as below:

$$Port\ Congestion_{it} = \beta_0 + \beta_1 Port\ Resilience\ Index_{i,t-1} + \beta_2 X_{i,t-1} + \beta_3 Port\ Congestion_{it2019} + \gamma_i + \mu_t + \varepsilon_{it} \quad (8)$$

Where *Port Congestion*$_{it}$ is port congestion of port i in month t, *Port Resilience Index*$_{i,t-1}$ is the resilience index of the port i, lagged by one month. $X_{i,t-1}$ represents for a vector of control variables of port i, lagged by one month. We also included the lagged port congestion at the same time of 2019 as repressors to make regression models be "dynamic" in nature, considering the persistent influence of past performance. γ_i is port fixed effects, controls for the unobserved time-invariant features which constant at each port. μ_t is month fixed effects, controls for the unobserved time-variant features, ε_{it} is the idiosyncratic error term.

4. Empirical analysis

To ensure the consistency and validity of the model estimation, we analyzed the multicollinearity of all variables before testing hypotheses. The variance inflation factors (VIF) for all variables are smaller than 10, thus indicating that the multicollinearity is not the main concern of the study. Table 3 presents the descriptive statistics and correlations.

4.1. Main analyses

Table 4 shows the ordinary least square (OLS) fixed-effects regression results using cargo throughput and port congestion as the dependent variables. All regression models control port-fixed and month-fixed effects. Models 1, 3, 5, and 7 report the base regressions in which only the independent variable (port resilience index lagged by one month) and fixed effects are included. Models 2, 4, 6, and 8 report the full regressions in which all the other control variables are included. In Model

Table 3
Descriptive statistics and correlation matrix.

Variables	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) FTCT	6.505	1.341	2.996	8.523								
(2) DTCT	7.443	0.494	5.472	8.889	0.250***							
(3) AWT	3.248	0.683	0	4.940	0.248***	0.053						
(4) SWP	3.135	1.147	0	5.147	0.341***	0.313***	0.634***					
(5) PRI	0.524	0.240	0.073	0.955	0.333***	0.428***	0.158***	0.367***				
(6) GDP	10.283	0.868	7.957	11.731	0.080*	0.188***	−0.129**	−0.027	−0.030			
(7) NCC	66.432	140.941	0	940	0.002	−0.076	−0.037	−0.049	0.011	−0.041		
(8) CPI	101.77	1.618	98.2	106.6	0.001	−0.118***	−0.026	−0.057	−0.070	−0.214***	0.239***	
(9) IAV	6.236	4.612	−15.9	23.2	−0.058	0.151***	0.151***	−0.090*	0.021	0.125**	−0.298***	−0.348***

Note: This table reports means, standard deviations, minimum values, maximum values, and Pearson correlation coefficients.
Note. FTCT = Foreign Trade Cargo Throughput, DTCT = Domestic Trade Cargo Throughput, AWT = Average Waiting Time, SWP = Ships Waiting at Port; PRI = Port Resilience Index; GDP = Gross Domestic Product; NCC = New Confirmed Cases; CPI = Consumer Price Index; IAV = Industry Added Value.
The Correlation Matrix is based on the First Difference of the Variables.
FTCT, DTCT, AWT, SWP, and GDP are log transformed.
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 4
Regression results of DTCT, FTCT, AWT, and SWP.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	DTCT		FTCT		AWT		SWP	
PRI (*t*-1)	−0.703	−0.983	1.223**	1.517**	−1.203*	−1.256*	−1.923*	−2.025*
	(0.579)	(0.551)	(0.506)	(0.581)	(0.689)	(0.644)	(1.012)	(1.046)
DTCT$_{2019}$		−0.076						
		(0.064)						
FTCT$_{2019}$				0.241*				
				(0.123)				
AWT$_{2019}$						0.003		
						(0.002)		
SWP$_{2019}$								−0.003
								(0.004)
NCC (*t*-1)		0.000		−0.000		−0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
CPI (*t*-1)		−0.040		0.019		−0.003		−0.095
		(0.025)		(0.032)		(0.148)		(0.123)
lnGDP (*t*-1)		1.360		0.233		−1.252		4.578
		(1.096)		(0.888)		(2.962)		(5.422)
lnPD (*t*-1)		−9.628		0.505		5.769		−35.731
		(7.598)		(6.208)		(20.082))		(37.809)
IAV (*t*-1)		0.002		0.003		0.009		0.005
		(0.003)		(0.003)		(0.012)		(0.008)
Port FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	237	237	235	235	238	238	236	236
R-squared	0.892	0.978	0.897	0.995	0.645	0.776	0.900	0.922

Note. FTCT = Foreign Trade Cargo Throughput, DTCT = Domestic Trade Cargo Throughput, AWT = Average Waiting Time, SWP = Ships Waiting at Port; PRI = Port Resilience Index; GDP = Gross Domestic Product; NCC = New Confirmed Cases; CPI = Consumer Price Index; IAV = Industry Added Value.
Robust standard errors in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

(1), the coefficient of *PRI (Port Resilience Index)* is −0.703 and is not statistically significant. In Model (2), the coefficient of *PRI (Port Resilience Index)* is −0.983 and is not statistically significant, when considering the domestic trade cargo throughput at the same period in 2019 and all the other control variables. The finding indicates that the port resilience does not have a significant effect on domestic trade cargo throughput. In Model (3), the coefficient of *PRI (Port Resilience Index)* is 1.223 and is statistically significant at the 5% level. In Model (4), the coefficient of *PRI (Port Resilience Index)* is 1.517, and stays statistically significant, when considering the foreign trade cargo throughput at the same period in 2019 and all the other control variables. The finding indicates that the port resilience positively affects foreign trade cargo throughput. In Model (5), the coefficient of *PRI (Port Resilience Index)* is −1.203 and is statistically significant at the 10% level. In Model (6), the coefficient of *PRI (Port Resilience Index)* is −1.256, and stays statistically significant, when considering the average waiting time at the berth at the same period in 2019 and all the other control variables. The finding indicates that the port resilience negatively affects the average waiting time at the berth. In Model (7), the coefficient of *PRI (Port Resilience Index)* is −1.923 and is statistically significant at the 10% level. In Model (8), the coefficient of *PRI (Port Resilience Index)* is −2.025, and stays statistically significant, when considering the average number of container ships waiting at the port at the same period in 2019 and all the other control variables. The finding indicates that the port resilience negatively affects the number of container ships waiting at the port.

Taken together, empirical results in Table 4 suggest that the port resilience index positively relates to foreign trade cargo throughput. Therefore, we could expect that a resilient governed port will have higher foreign trade cargo throughput compared to other ports with less resilient systems, *ceteris paribus*.

Meanwhile, empirical results also suggest that the port resilience index negatively relates to the average waiting time for ships at the port, and the average number of ships waiting at the port. Therefore, we could expect that a resilient governed port will have less ships waiting, as well as shorter waiting times for ships berthing in port. That is, a resilient governed port will have less port congestion compared to other ports with less resilient systems, *ceteris paribus*.

4.2. Robustness test

We further ran several robustness checks to confirm the overall validity of our main findings. First, we extended our research sample. In addition to the year 2020, we included the year 2021, extending our research sample to 438 port-month observations. Second, we adopted the Instrumental Variables two-stage least-squares (IV-2SLS) to address the endogeneity concerns. The IV estimation requires the "excluded" instrumental variable influences the first-stage equation but not the second-stage equation (Angrist and Pischke, 2009). Based on suggestions from prior studies (Girard, 2010; Hein et al., 2022; Komugabe-Dixson et al., 2019), we use local government service as our "excluded" instrumental variable, which measures the comprehensive urban social services in the focal port's local city. The local government service score is available for all Chinese major cities and is based on eight elements of government service, including policies related to daily life, business environment, living environment, transportation services, education level, Medicare service, poverty alleviation, and the convenience of public services. We adopted this score from China's Urban Digitalization report.[2]

To study the effect of the port resilience index — instrumented by the local government service score — on the port throughput and congestion, we use two-stage least squares (2SLS). Table 5 reports the result of the robustness test. In the first stage, we regress the port resilience index on the local government service score. Model (1) reports the first-stage regression result. As is shown, the local government service score leads to a significant increase in the port resilience index. The corresponding *F*-statistic is 17.2, which lies well above (Staiger and Stock, 1994) threshold for "strong" instruments. Model (2) reports the second-stage regression result of DTCT. The coefficient of the (instrumented) port resilience index is −0.109, which remains not significant, suggesting that port resilience does not significantly affect the domestic trade cargo throughput of ports. Model (3) reports the second-stage regression result of FTCT. The coefficient of the (instrumented) port resilience index is 0.579, which is somewhat smaller than the OLS coefficient in Table 4. Importantly, it remains statistically significant, suggesting that the positive relationship between the port resilience index and the foreign trade cargo throughput is not driven by the endogenous choice of port governance. Model (4) reports the second-stage regression result of AWT. The coefficient of the (instrumented) port resilience index is −0.777, which is somewhat smaller in magnitude than the OLS coefficient in Table 4. Importantly, it remains statistically significant, suggesting that the negative relationship between the port resilience index and the average waiting time for cargos at the port is not driven by the endogenous choice of port governance. Model (5) reports the second-stage regression result of SWP. The coefficient of the (instrumented) port resilience index is −1.443, which is somewhat smaller in magnitude than the OLS coefficient in Table 4. Importantly, it remains statistically significant, suggesting that the negative relationship between the port resilience index and the number of cargo waiting at the port is not driven by the endogenous choice of port governance. Overall, the results presented in Table 5 are supportive of main findings that ports with higher resilience index are more likely to be awarded with more foreign trade cargo during the pandemic. Meanwhile, ports which are not resilient enough will face worse port congestion during the pandemic.

Table 5
Robustness test: IV-2SLS.

	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent variables	PRI First-stage	DTCT	FTCT	AWT	SWP
PRI	0.037***				
	(0.011)				
PRI (instrumented)		−0.109	0.579**	−0.777**	−1.443**
		(0.198)	(0.262)	(0.384)	(0.610)
Controls	Yes	Yes	Yes	Yes	Yes
Port FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Wald exogeneity Chi-Squared Test		18.36***	18.99***	18.24***	17.98***
Sargan-Hansen test of over identification		0.338	0.353	0.192	0.233
Observations	438	437	437	431	431
R-squared	0.924	0.916	0.992	0.978	0.876

Note. FTCT = Foreign Trade Cargo Throughput, DTCT = Domestic Trade Cargo Throughput, AWT = Average Waiting Time, SWP = Ships Waiting at Port; PRI = Port Resilience Index; GDP = Gross Domestic Product; NCC = New Confirmed Cases; CPI = Consumer Price Index; IAV = Industry Added Value.
Robust standard errors in parentheses.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

4.3. Additional analyses

Next, we turn to explore an alternative port resilience index to reflect port governance before COVID-19. Our extension has practical implications that with China's sudden COVID reopening in December 2022, the new infection surge in China is seriously affecting major ports. For instance, the port of Shanghai, the world's number one container port, is experiencing increased congestion. During the first week of 2023, the average vessel TEU (twenty-foot equivalent unit) capacity waiting out of port limits (as an indicator of port congestion) was 321,989 TEUs, the highest amount recorded since April 2022. Since China has ended "zero COVID" so quickly, it is unlikely that China will sustain the same government response activities to COVID control and prevention. Therefore, we established an alternative port resilience index during 2017–2019 and examined the impact of the alternative port resilience index on port governance performance. We leave it for future research, which resilience index will reflect China's practices more.

Specifically, we replaced the government response to the COVID-19 index with weather radar observation sites.[3] As indicated by previous studies, the local weather service represents the local government's infrastructure resilience facing threats from extreme weather (Hosseini and Barker, 2016). Furthermore, with more weather radar observation sites, the local government can better mitigate the impact of adverse weather events in advance, therefore the local port will be more resilient in the event of weather disruptions (Gharehgozli et al., 2017).

Meanwhile, to further reflect the importance of local infrastructure in building a resilient port system, we added the local province's completed fixed assets investment[4] as another indicator. Prior literature has stated that fixed assets investment, especially in terms of transportation and logistics, reflects the local investment in infrastructure, which reflects the transportation system's optimal performance. In a

[2] http://deindex.h3c.com/2022/Release/.

[3] The number of local weather radar observation sites is an annual number extracted from the National Bureau of Statistics of the People's Republic of China (http://www.stats.gov.cn/).

[4] Completed fixed assets investment is monthly number adopted from the National Bureau of Statistics of the People's Republic of China (http://www.stats.gov.cn/).

region with higher investment in fixed assets, ports are more likely to enjoy a reliable and convenient transportation system; thus, the port-hinterland container transportation network is much more resilient (Chen et al., 2018).

In addition, the “smart port” and the “national logistics hub” were both initiated in 2019. These two indicators, thus, cannot fully reflect resilience from the perspective of port operations. We used two indicators to replace the smart port and national logistics hub before COVID-19. One is the number of berths of the port, and the other is the dock length for the production of the port.[5] As indicated by previous studies, the local weather service represents the local government's infrastructure resilience facing threats from extreme weather (Hosseini and Barker, 2016). With more weather radar observation sites, the local government can better mitigate the impact of adverse weather events in advance. Therefore, the local port will be more resilient in weather disruptions (Gharehgozli et al., 2017).

Combining the above indicators, we created an alternative port resilience index, excluding indicators related to response to the pandemic. We added indicators that reflect the port's resilience in daily operations and in the face of adverse weather threats. We then applied the same four-stage entropy weight method (EWM) reported in section 3.3.1 to calculate the alternative PRI. The final result shows comparative consistency with the original PRI. Table 6 reports the port ranking in the alternative resilience index before COVID-19. Comparing the two alternative PRIs before and post-COVID-19 shows inspiring results. With Ningbo-zhoushan port staying as one of the most resilient ports regardless of the pandemic, most ports showed different resilience before and after COVID-19. For instance, due to their highly effective government response, Tianjin, Nanjing, and Guangzhou improve their resilience during and post the COVID-19. Whereas Tangshan and Cangzhou, two ports both located in Hebei province, although show high resilience before COVID-19, fell much behind during the pandemic, due to less effective government responses, as well as relatively lower information construction level, due to their lack of status as national logistics hubs to build smart ports.

Subsequently, we further investigated the effect of the alternative PRI on port throughput during 2017–2019. The regression result is distinctive (coefficient = 0.045, n.s. with FTCT; coefficient = 0.714, sig. at 1% level with DTCT) with PRI post-COVID-19. The result indicates that before COVID-19, the alternative port resilience index positively affects the domestic trade cargo throughput.

5. Discussion

5.1. Theoretical contributions

This paper contributes to several literature streams. First, this paper answers the recent call for establishing a robust port resilience index based on a systematic view (Verschuur et al., 2022). This paper adopts a multi-stakeholder view to establish a port resilience index that can be used in the cross-port comparison. Prior literature has proposed several dimensions for port resilience while needing a systematic framework to classify these separated, seemingly unrelated dimensions into a unified category. To resolve the above question, this paper takes an integrated port-hinterland-local government framework to examine port resilience. This paper first chooses three indicators——port governance efficiency, whether the port is a smart port, and a national logistics hub to reflect how well the port is resiliently governed in the post-COVID-19 era. Meanwhile, as prior literature also suggests that the hinterland is one essential stakeholder in port governance (Chen et al., 2017), this paper further chooses two indicators——ICT infrastructure and digital industrial convergence of the hinterland to reflect the resilience of port-hinterland in the post-COVID-19 era. In addition, recent studies have verified the importance of local city governance to port resilience (Hein et al., 2022; Komugabe-Dixson et al., 2019). Especially in the post-COVID-19 era, how effectively the local government responds to the pandemic and the capability of local government to sustain the normal operations of the whole society become the critical enabling factor in building a resilient port system. Therefore, this paper chooses two indicators——the government response to COVID-19 and the local governance score to reflect the resilience of the port-local government in the post-COVID-19 era.

Second, this paper answers the research question of the meaning of port resilience in the post-COVID-19 era in an empirical way. This paper examines the direct effect of the port resilience index on port throughput and congestion, two of the most critical indicators of port governance performance. The results indicate that a resilient port will witness a higher throughput while lower congestion, suggesting that a resilient system will enable ports to adapt to unexpected challenges posed by the global pandemic while maintaining better performance than counterparts.

5.2. Practical implications to port governance

This paper also provides insightful implications for port governance practices. In the post-COVID-19 era, this paper indicates the importance of large ports to sustain a regular, well-organized, and resilient port governance system. Port decision-makers are responsible for enhancing port resilience to manage risks and threats to achieve minimum downtime when facing unexpected emergency events (McIntosh and Becker, 2019). This paper can provide a guideline for port decision-makers. Specifically, this paper suggests that port decision-makers should speed up the construction of resilient and smart ports. Although using big data and other digital technologies in China has played a crucial role in the fight against COVID-19, Chinese ports are experiencing more intense challenges recently with the new COVID surge in early 2023. Therefore, advanced digital technologies, such as non-invasive visual inspection and detection systems, and intelligent pattern recognition systems, should be adopted with AI and big data to help build early-warning and epidemic prevention and control systems in ports.

Meanwhile, this paper can provide practical suggestions for policy-makers. This paper suggests that the local government should actively improve the integration between the port and the hinterland. It is necessary to improve the connectivity between the port and other transportation systems, including roads, railways, airways, inland waterways, and pipelines, to improve the turnover efficiency of goods and reduce port congestion. Furthermore, it is highly beneficial to strengthen the information sharing and interconnection between the port and the hinterland to utilize the intermodal transportation system's complementary advantages fully. This paper also suggests the importance of increasing government efficiency and adopting technological innovation, especially in digital technologies, to build “smart ports” for local government. Also, this paper suggests the importance of digital technologies to port-hinterland resilience. In order to improve the port-hinterland integration to build a resilient port system, this paper suggests that ICT technologies, such as blockchain, big data, and artificial intelligence, should be widely utilized in hinterland operations.

5.3. Limitations and future research

This study still has several limitations which provide avenues for future research. Firstly, this study only chooses Chinese ports as the research sample due to data availability. Although considering the differences between statistical methods and criteria in different countries, it is hard to establish a cross-country resilience index system. Future research may still explore adopting similar stakeholders to calculate a comparable port resilience index for different countries to further enhance this study's external generalizability. Secondly, due to data

[5] These two are annual numbers adopted from China Marine Statistical Yearbook.

Table 6
The port ranking in the alternative resilience index before the COVID-19.

Ports	PRI in 2017	PRI ranking in 2017	PRI in 2018	PRI ranking in 2018	PRI in 2019	PRI ranking in 2019	Upward trend
Ningbo-zhoushan	0.747846842	1	0.750180483	2	0.774116233	3	
Shanghai	0.742299442	2	0.784369083	1	0.809946208	1	
Tangshan	0.636016967	3	0.737958283	3	0.774821867	2	✓
Cangzhou	0.513566517	4	0.576750158	4	0.617054367	4	
Qinhuangdao	0.512940050	5	0.266407808	12	0.305207658	11	✓
Qingdao	0.420529850	6	0.327790875	9	0.334770717	9	
Yantai	0.413784017	7	0.407826850	6	0.392065975	6	
Guangzhou	0.412962092	8	0.363737075	7	0.374235275	7	
Shenzhen	0.374925775	9	0.430425525	5	0.409895492	5	
Zhanjiang	0.352725708	10	0.321830867	10	0.295560167	12	
Dongguan	0.306805550	11	0.340129192	8	0.323210817	10	
Taizhou	0.282397483	12	0.275017967	11	0.341825142	8	✓
Nantong	0.198279375	13	0.202275083	14	0.210667125	16	
Nanjing	0.127359358	14	0.149462992	17	0.190942467	17	
Zhenjiang	0.121162175	15	0.186560475	16	0.24249485	13	✓
Beihai	0.103977775	16	0.213707375	13	0.224239758	14	
Dalian	0.094162408	17	0.191532625	15	0.216946108	15	
Fuzhou	0.076000683	18	0.046708075	22	0.046236867	22	
Xiamen	0.061988425	19	0.077484575	21	0.073964625	20	✓
Chongqing	0.059532858	20	0.108815942	18	0.147489292	18	
Tianjin	0.042682933	21	0.092178258	19	0.066871083	21	
Jiujiang	0.031087258	22	0.081172092	20	0.098981192	19	✓

Note. PRI = Port Resilience Index.

availability, this study mainly uses 2020–2021 as the research window. Future research can further extend the port resilience index to 2022 to verify this study's reliability.

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.

Data availability

Data will be made available on request.

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