Lower volatility, lower profit? Smart trap in two-dimensional port competition

Abstract: Ports face growing demand volatility and congestion, threatening operational efficiency and environmental performance. AI-powered smart port technologies promise to mitigate these challenges by making congestion information visible to port users. However, this paper shows that such visibility does not always deliver the expected benefits when ports compete on both price and congestion situations. Providing more congestion information may paradoxically amplify demand fluctuations and worsen congestion, a phenomenon we term the "smart trap." We further show that the value of developing smart port depends critically on port capacity levels and their demand correlation. When port capacity is tight and demand is moderately correlated, developing smart port can increase congestion and emissions. Our analysis cautions that digitalization does not universally improve port sustainability, and this finding is verified by an empirical study using Hamburg and Bremerhaven port data.

Keywords: Port congestion; Demand volatility; Smart technology adoption; Sustainable maritime operations; Port competition

1. Introduction

Ports are critical nodes connecting maritime and inland transportation systems, and their operational performance plays a central role in sustaining global supply chains and hinterland logistics networks. Yet port operations are inherently exposed to substantial demand volatility, driven by global trade fluctuations, shipping alliance adjustments, and macroeconomic shocks (Bai et al. 2022; Shi et al. 2023b). When such random demand interacts with constrained service capacity (i.e., physical upper bound on a port's throughput, encompassing berth availability, yard space, and handling equipment), congestion emerges as a persistent challenge. It has been reported that port congestion leads to prolonged berth waiting times and inefficient cargo handling (Wang et al. 2021; Shi et al. 2023a), which are widely recognized as a key contributor to excessive fuel consumption and air pollution in maritime transportation systems (Li et al. 2024; Wang et al. 2024a). These pressures not only undermine ports' profitability and resilience but also expose the limitations of traditional, experience-based decision-making in port sustainable operations that aim to maintain service performance while minimizing environmental externalities. Indeed, many ports continue to rely on legacy tools such as spreadsheets to manage critical services, leaving them vulnerable to demand volatility and slow operational responses (Luo et al. 2016; Offshore Energy 2021; Yan et al. 2021).

Against this backdrop, smart port development that leverage big data, real-time monitoring, and artificial intelligence (AI) have gained prominence as a potential remedy for demand volatility and sustainability challenges (Choi and Shi 2022; S&P Global 2023). By enhancing demand forecasting accuracy and making congestion information more transparent to port users (Yan and Wang 2022; Port Technology 2022), smart ports promise a transition from reactive experience-based operations toward proactive, AI-powered traffic management. Figure 1 illustrates this transformation using the Port of Rotterdam's real-time port monitoring dashboard, where vessel arrivals, traffic density, and congestion externalities are continuously updated and visible to port users (Port of Rotterdam 2026). From a sustainability perspective, AI-enabled congestion mitigation holds the promise of reducing emissions (S&P Global 2023). Thus, smart port technologies represent not merely an operational upgrade but a strategic pathway toward environmentally sustainable maritime operations.

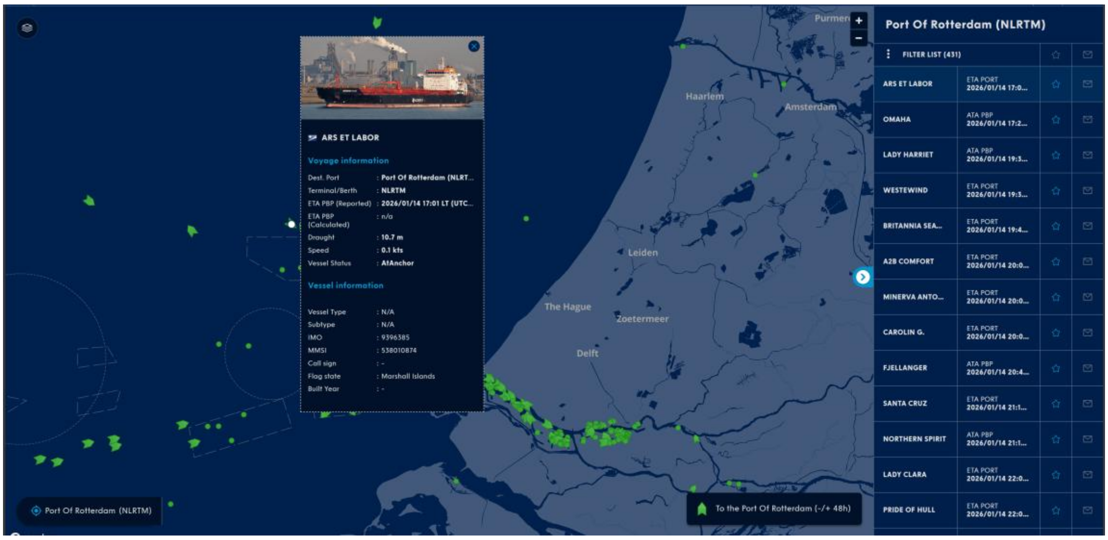


Figure 1. The real-time port monitoring dashboard for the Port of Rotterdam

Having said that, ports usually compete within interconnected traffic networks for overlapping hinterland demand. So, the benefits of smart port development, both economic and environmental, are far from guaranteed once competitive interactions are taken into account. In such environments, improving congestion information visibility does not merely enhance unilateral decision quality. Meanwhile, it reshapes strategic interaction among ports and alters port users' service choice behavior (Universal Cargo 2021; UNCTAD 2022). On the service side, more accurate demand information enables ports to adjust service prices more responsively to anticipated congestion, potentially intensifying price competition (Zheng et al. 2020). On the demand side, real-time congestion information visibility allows port users to flexibly choose ports with lower congestion levels (Notteboom et al. 2022). While individually rational, such behavior can generate negative externalities: users' attempts to avoid congestion at one port may concentrate traffic at competing ports, thereby exacerbating system-wide congestion (Feng 2025). For instance, due to surging demand at Singapore port and service delays, some port users have opted for nearby ports like Port Klang in Malaysia, increasing these ports' throughput (E-PORTS 2025). Rather than resolving the problem, this transparency-driven reallocation concentrated demand at competing ports. Antwerp's berth waiting times surged 37% within weeks, and Hamburg's rose 49%, producing new congestion cascades across the network (The Cooperative Logistics Network 2025). More broadly, industry analysts now routinely recommend port diversification as a response to congestion visibility. They advise shippers to reroute to less congested ports such as Laem Chabang or Busan based on real-time congestion data (TRADLINX 2025). As such, micro-level rationality may induce macro-level inefficiency, eroding the very resilience gains that smart technologies aim to deliver.

This tension gives rise to what we refer to as the "smart trap" paradox in port operations. *At the signal level*, more accurate congestion information may paradoxically amplify the perceived congestion disutility of port users when demand shocks are correlated. *At the market-outcome level*, this signal level distortion transmits into equilibrium demand fluctuations as ports adjust prices and port users reallocate traffic, potentially intensifying congestion-driven competition[1] rather than alleviating it. *At the strategic-adoption level*, anticipation of these adverse consequences can deter individually rational ports from investing in smart technologies, leading to coordination failures even when joint smart port developments would be a Pareto-optimal outcome.

A striking example occurred during the 2025 European port crisis. Once real-time tracking platforms made Rotterdam's severe congestion transparent to all market participants, Maersk removed Rotterdam from its transatlantic service and rerouted vessels to Hamburg, while MSC and CMA CGM similarly diverted vessels to less congested alternatives (The Cooperative Logistics Network 2025). Indeed, industry reports document widespread hesitation among ports to invest in smart port development, opting instead to maintain relatively closed information systems despite the existence of advanced digital technologies (Offshore Energy 2021). Such reluctance highlights a fundamental governance challenge: without appropriate incentives or coordination, technology-driven transparency may backfire in connecting traffic systems, undermining both profitability and sustainability goals.

Port congestion is itself a well-documented driver of excess emissions in maritime transport systems (Li et al. 2024). During the 2021 congestion crisis at the Ports of Los Angeles and Long Beach, idle vessels at anchorage generated over 100 tons of air pollutants per day, equivalent to the emissions of approximately six million cars (Long Beach Post 2021; Vukić and Lai 2022). Motivated by this paradox and recognizing that any competitive mechanism affecting port congestion carries direct environmental consequences, this study addresses two

[1] This refers to the competition between ports that arises when any port develops smart port, which enables port users to observe (or infer) congestion conditions and reallocate traffic toward ports with lower congestion levels.

fundamental research questions: (i) Does smart port development necessarily mitigate demand volatility, congestion, and associated environmental impacts in competitive port systems? (ii) How do demand volatility and service capacity interact to determine whether AI-powered smart port development improves or undermines sustainability? Addressing these questions is essential for ensuring that investments in AI-powered digital technologies translate into genuine benefits for both port operations and port users.

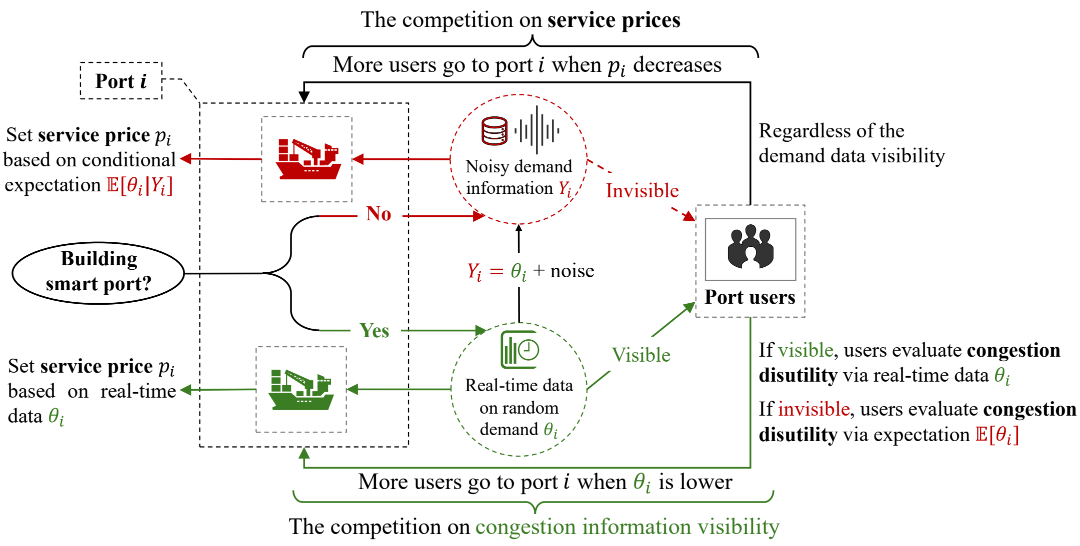


Figure 2. The illustration of two-dimensional competition between ports

To answer these questions, we develop a game-theoretical model of two symmetric competing ports with service capacity upbound that face random demand shocks. The random parts of demand are imperfectly observed by ports through noisy signals and are positively correlated, reflecting shared exposure to global trade conditions (Verschuur et al. 2022). Each port decides whether to develop a smart port that improves information accuracy and makes the random part of demand visible to port users. This strategic choice fundamentally alters both ports' pricing behavior and port users' service selection decisions. As a result, ports compete along two dimensions: service prices and congestion information visibility (see Figure 2).

Our analysis yields several counterintuitive insights with important implications for sustainable maritime transportation. First, even when two ports are symmetric in their service capacities and initial information accuracies, asymmetric equilibria can emerge in which only one port develops smart port to gain the information advantage, while its rival paradoxically benefits from mitigated price competition without bearing investment costs. This finding reveals how AI-enabled transparency creates new strategic asymmetries even among identical competitors. Second, we uncover a Prisoner's Dilemma in developing smart port, where neither port invests in AI technologies despite joint smart port developments improving both profitability and reducing system-wide congestion. This coordination failure harms port profitability, as port users suffer from higher congestion disutility and the maritime system experiences elevated emissions. Third, our environmental impact analysis reveals that smart port development does not universally benefit sustainability. When service capacity is insufficient and the correlation of demand random parts is moderate, joint smart port developments may paradoxically increase environmental externalities by intensifying congestion-driven competition. We identify conditions under which AI-powered transparency aligns with or conflicts with sustainability goals, providing actionable guidance for when capacity expansion should complement technology investments.

The remainder of this paper is organized as follows. We review the most relevant literature in Section 2. Section 3 introduces the model setting and assumptions. We analyze the equilibrium outcomes in Section 4 and then compare the two ports' performances at risk (both demand volatility and profitability) and their environmental impacts under different strategies. Section 5 applies the model to the Port of Hamburg and the Port of Bremerhaven using actual throughput data to validate the theoretical predictions. Section 6 concludes this paper and discusses future research directions. All proofs are provided in the Appendix.

2. Literature Review

Our study lies at the intersection of three streams of literature: (1) port competition and congestion management, (2) demand information management, and (3) green and sustainable maritime operations. For each stream, we summarize the existing contributions and identify the specific gaps that our study addresses. A detailed comparison of representative studies and our contributions is provided in Appendix E.

2.1 Port Competition and Congestion Management

Early port competition research conceptualizes ports primarily as geographically differentiated service providers competing on price (Song and Yeo 2004). Song et al. (2016) extend this view by introducing transport chain dynamics, capturing dual rivalry across transshipment and hinterland markets. A growing body of subsequent work moves beyond price-based competition to examine non-price competitive dimensions. Ishii et al. (2013) demonstrate that differentiated service capabilities lead to substantially different equilibrium pricing and capacity investment strategies compared to homogeneous service scenarios. Heilig et al. (2017) show that information sharing serves as both a competitive lever and a coordination challenge in digitalized port environments. Pujats et al. (2020) synthesize these developments, confirming that service differentiation becomes a prevalent modeling construct. More recent studies further examine the role of carrier alliances in shaping port competition. Liu and Wang

(2019) demonstrate that horizontal alliances among carriers can rebalance bargaining power within the transport chain, while Wang et al. (2024b) caution that such alliances may transition from win-win to lose-win outcomes under capacity constraints.

Closely intertwined with port competition is congestion management, which has shifted from treating congestion as an exogenous operational cost (Liu et al. 2014; Tan et al. 2015) toward recognizing it as an endogenous outcome of strategic interactions. Tao et al. (2023) propose workload balancing protocols to internalize traffic congestion within terminal operations. Liu et al. (2023a) develop a simulation-based framework to evaluate smart regulations for pandemic-induced congestion. Going further, Niu et al. (2024a) reveal that smart port investments can induce a “Matthew effect”, where large-scale ports capture disproportionate market shares, potentially exacerbating congestion at smaller nodes. Data-driven approaches are also developed to forecast volatile port demand and support risk management (Yan et al. 2025a, 2025b), and Niu and Ruan (2023) study self-reliant shipping strategies to reduce logistics and congestion risks.

Despite this evolution toward multidimensional competition, existing studies largely treat information as either a coordination tool or a static differentiation factor. Few studies simultaneously capture how congestion information visibility reshapes both port pricing behavior and port users' service selection decisions. Our study fills this gap by introducing a two-dimensional competition framework in which ports compete on both service prices and congestion information visibility. We show that smaller service capacity weakens price competition while intensifying congestion-driven competition, and reveal that asymmetric equilibria and a Prisoner's Dilemma can emerge even among symmetric ports.

2.2 Demand Information Management

The challenge of managing demand uncertainty attracts sustained attention across operations management and maritime economics. Guo and Jiang (2016) develop an analytical framework to study how consumer inequity aversion affects firms' pricing and quality decisions under uncertainty. Shen and Chan (2017) emphasize that while big data enables more accurate predictions, the value of sharing such information is contingent on incentive alignment among supply chain partners. Risk attitudes further complicate these dynamics: Zhuo et al. (2021) employ mean-risk analysis to demonstrate that risk-averse carriers tend to lower prices and adopt conservative capacity strategies during periods of high volatility. In the maritime context specifically, Huang et al. (2023) examine how liner companies' use of big data for demand forecasting impacts competitiveness and consumer surplus. A parallel stream of research focuses on resilience under disruptions (Guikema 2020; Macrae 2025).

On the technology side, Yang et al. (2019, 2021) systematically analyze the utility of AIS-based big data systems for maritime research, while highlighting critical issues regarding data accuracy and destination reporting integrity. Emerging technologies further reshape the competitive landscape. Wang et al. (2021) model port logistics capability investments and reveal that blockchain adoption incentives are tightly coupled with market competition intensity. Shi et al. (2023c) examine how blockchain-enabled platforms facilitate quality traceability and reduce transaction costs. Niu et al. (2024b) find that drone technologies intensify competition, while stricter airspace regulation may paradoxically increase carrier profits.

While the technology adoption literature has examined how individual technologies enhance operational efficiency, and the demand uncertainty literature has established the value of information sharing, neither stream addresses how information disclosure to end users fundamentally reshapes competitive dynamics between service providers. Our study bridges this gap by modeling a bi-parallel information structure in which demand information from both ports directly affects port users' service selection. We identify the dual role of smart ports' congestion information: on the service side, accurate information allows ports to adjust prices more responsively; on the demand side, it provides port users with more precise congestion assessments. This dual role gives rise to what we term the "smart trap," in which improving information accuracy paradoxically amplifies demand volatility under certain conditions.

2.3 Green and sustainable maritime operations

The imperative to decarbonize maritime transport intensifies markedly over the past decade. Cariou and Cheaitou (2012) compare the effectiveness of a European speed limit versus an international bunker levy, demonstrating that the choice of policy instrument significantly affects emission reduction outcomes. Bektaş et al. (2019) provide a comprehensive overview of how operational research methodologies have been applied to green freight transportation, highlighting the critical role of analytical models in evaluating trade-offs between efficiency and environmental performance. Within ports specifically, Lim et al. (2019) identify persistent challenges in measuring and benchmarking environmental performance across heterogeneous port systems, while Wang et al. (2020) demonstrate that co-opetition governance structures can enhance port-level green efficiency. At the carrier level, Liu et al. (2025) show how environmental regulation, demand uncertainty, and competition jointly influence the timing and scale of green technology investments. Wu et al. (2026) further reveal how geopolitical disruptions interact with carbon policies to reshape decarbonization incentives.

A second and increasingly important line of inquiry examines the environmental externalities generated by port congestion. Li et al. (2024) provide direct empirical evidence that port congestion significantly increases shipping emissions in Chinese ports, establishing a quantitative link between operational inefficiency and environmental degradation. Wang et al. (2024a) highlight both the promise and the implementation barriers of shore power adoption for reducing at-berth emissions. Importantly, the assumption that digital technologies inherently improve sustainability warrants scrutiny. Niu et al. (2026) show that AI-based shipment consolidation may generate hidden emissions and incentive distortions, cautioning against uncritical optimism about digitalization.

The existing sustainability literature has not systematically examined how smart port development affects environmental outcomes under competitive conditions. Our study addresses this gap by analyzing the environmental impact of smart port development across different equilibrium configurations. We show that joint smart port development does not universally improve sustainability: when service capacity is insufficient and demand correlation is moderate, it may paradoxically increase environmental externalities. We identify conditions under which AI-powered transparency aligns with or conflicts with sustainability goals, providing actionable guidance for policymakers seeking to coordinate digital transformation with environmental objectives.

3. Model Settings

Consider two competing ports, denoted by $i \in \{A, B\}$, located within the same connecting traffic system and serving overlapping hinterland demand. Each port provides cargo-handling services subject to a service capacity K, which captures constraints such as berth availability, yard space, and handling equipment. We first describe the demand structure of port services.

3.1 Demand Structure of Port Services

Port demand is decomposed into two components: (i) a deterministic part that reflects port users' predictable service choice behavior; and (ii) a random part that captures aggregate demand uncertainty.

We model the deterministic part using a Hotelling framework, which is widely adopted in port traffic operations (see e.g., Shi et al. 2023a; Wang et al. 2021). Port users are distributed along the unit interval connecting two ports which reflects heterogeneous access costs, geographic dispersion, or idiosyncratic port preferences within the hinterland (Niu et al. 2024a). These port users generate a stable flow of traffic whose allocation across ports depends on service prices and anticipated congestion. Let d_i denote the deterministic part of port i's demand, endogenously determined through competitive port choice.

In addition, each port faces random part of demand that is not directly attributable to predictable port user decisions. This random component captures uncertainty arising from macroeconomic shocks, trade cycle volatility, and schedule unreliability (Bai et al. 2022; Shi et al. 2023b). We denote this random part of port i's demand by θ_i.

Accordingly, the total realized demand at port i is given by $D_i = \theta_i + d_i$. This demand structure reflects the reality that realized port throughput fluctuates around a predictable baseline even when pricing and port choice behavior are well understood.

3.2 Demand Information Structure

The random part of demand θ_i follows a normal distribution $\theta_i \sim \mathcal{N}(\mu, \sigma^2)$, where $\mu(> 0)$ represents the expected level of the random part of demand and σ^2 captures the magnitude of such random demand. Because ports located in the connecting traffic system are exposed to common economic conditions and often serve overlapping shipping networks, the random parts faced by the two ports are correlated. We capture this by a positive correlation coefficient $\rho > 0$, such that $\mathrm{Cov}(\theta_A, \theta_B) = \rho$.

To improve resilience, particularly by mitigating the demand volatility, ports may adopt smart technologies to improve demand data accuracy and congestion information visibility to port users. Let $S_i \in \{T, N\}$ denote port i's decision regarding smart port development, where T indicates development and N indicates non-development. The joint strategy profile is therefore $(S_A, S_B) \in \{(N,N), (T,N), (N,T), (T,T)\}$, which we denote by the superscripts NN, TN, NT, TT, respectively.

When port i does not develop smart port ($S_i = N$), port i itself observes an imperfect signal Y_i of its random part θ_i. The signal can be obtained through historical data and is unbiased (i.e., $\mathbb{E}[Y_i|\theta_i] = \theta_i$). Following Ericson (1969), we define signal accuracy as $t_i \doteq \frac{1}{\mathbb{E}[Var(Y_i|\theta_i)]}$ such that a higher value of t_i correspond to more precise demand signal. The posterior expectation of random demand conditional on the observed signal is given by

$$\mathbb{E}[\theta_i|Y_i] = \frac{t_i\sigma^2}{1+t_i\sigma^2} Y_i + \left(1 - \frac{t_i\sigma^2}{1+t_i\sigma^2}\right) \mathbb{E}[\theta_i], \tag{1}$$

which is a weighted average of the signal Y_i and the prior mean $\mathbb{E}[\theta_i]$. As signal accuracy increases, greater weight is placed on the realized signal. In the case of perfectly accurate information, $\lim_{t_i\to\infty} \frac{t_i\sigma^2}{1+t_i\sigma^2} = 1$ such that $\lim_{t_i\to\infty} \mathbb{E}[\theta_i|Y_i] = Y_i$. For analytical tractability, we assume signal accuracy across ports to be $t_A = t_B = t > 0$.

When port i develops smart port ($S_i = T$), demand information will be visible to port users. Usually such demand information is noiseless. We can show that letting the demand information be imperfect will not change the main insights. Then the improvement in information accuracy through smart port development is defined as $\mathcal{R} \doteq 1 - \frac{t\sigma^2}{1+t\sigma^2} = \frac{1}{1+t\sigma^2}$. A higher value of $\mathcal{R}$ indicates a greater degree of information accuracy improvement through smart port development.

3.3 Port Users' Choice Decisions

Depending on the strategy matrix of the two ports, congestion disutility and port users' choice decisions are different in four scenarios.

In scenario (N, N), as neither port develops smart port, port users can only assess port congestion based on expected traffic volumes. As such, their congestion disutility can be calculated by a volume-capacity ratio $\lambda\frac{\mathbb{E}[D_i]}{K}$, where λ measures the aversion of port users to congestion, and K denotes the service capacity. That is, the ratio $\mathbb{E}\frac{[D_i]}{K}$ serves as a likelihood for the expected congestion level at the port. Such cost is widely employed in the port and transport economics literature (see e.g., Álvarez-SanJaime et al., 2015; Bae et al., 2013). Obviously, a smaller K or a larger λ amplifies the aversion from congestion.

Following Liu and Tyagi (2011) and Wang et al. (2021), we assume a Hotelling line where port users are uniformly distributed in the interval $[0, 1]$ and choose between two ports according to their utilities. In particular, a port user located at $x \in [0,1]$ derives the following utility from port i's service:

$$U_i(x) \doteq \begin{cases} v - \gamma x - p_A - \lambda \frac{\mathbb{E}[D_A]}{K}, & \text{if } i = A \\ v - \gamma(1 - x) - p_B - \lambda \frac{\mathbb{E}[D_B]}{K}, & \text{if } i = B \end{cases}, \tag{2}$$

where v denotes the port users' basic utility for port services, γ is the unit transportation cost along the interval between two ports, p_i is the service price charged by port i.

In practice, port service charges comprise a fixed base charge (e.g., terminal handling charges, wharfage fees) that is typically set through long-term contracts or published schedules, plus a variable congestion-responsive component (e.g., port congestion surcharges, peak-period premiums, dwell-time penalties) that ports adjust based on anticipated or realized congestion conditions. The service price p_i in our model corresponds to this variable component. The fixed base charge is absorbed into the unit handling cost h. Since the fixed component does not vary with congestion and cancels out in port users' comparative decisions, the equilibrium analysis is mathematically equivalent to the full two-part pricing structure (i.e., the fixed base charge plus the variable fee).

The marginal port user who is indifferent between the two ports in scenario (N, N) is located at $\tilde{x}^{NN} \doteq \frac{1}{2} - \frac{K(p_A - p_B)}{2(\lambda + K\gamma)}$. It follows that port users within the interval $[0, \tilde{x}^{NN}]$ choose port A's service while those within the interval $[\tilde{x}^{NN}, 1]$ choose port B's service, resulting in the demand volumes $d_A^{NN} = \tilde{x}^{NN}$ and $d_B^{NN} = 1 - \tilde{x}^{NN}$. Anticipating d_i^{NN}, two ports simultaneously determine the service prices p_i based on their demand signals Y_i to maximize posterior profits:

$$\pi_i^{NN} = \mathbb{E}_{\theta_i}[(p_i - h)\left(\theta_i + d_i^{NN}\right)|Y_i], \tag{3}$$

where $h(> 0)$ is the unit handling cost of port services.

In scenario (T, N), port A's congestion information is visible to port users such that port users can better evaluate the congestion disutility. Port users can also infer port B's congestion degree due to the correlation of the two ports' demand random part (i.e., $\mathrm{Cov}(\theta_A, \theta_B) = \rho$). That is, their evaluation of congestion disutility by choosing port A's service becomes $\lambda \frac{D_A}{K}$, while those by choosing port B's service become $\lambda \frac{\mathbb{E}_{\theta_B}[D_B|\theta_A]}{K}$. As a result, the indifferent point in scenario (T, N) is derived as $\tilde{x}^{TN} = \frac{1}{2} + \frac{\lambda(1-\rho)(\mu-\theta_A)}{2(\lambda+K\gamma)} - \frac{K(p_A-p_B)}{2(\lambda+K\gamma)}$. Anticipating the demand volumes $d_A^{TN} = \tilde{x}^{TN}$ and $d_B^{TN} = 1 - \tilde{x}^{TN}$, two ports maximize their posterior profits:

$$\begin{cases} \pi_A^{TN} = (p_A - h)(\theta_A + d_A^{TN}) - F \\ \pi_B^{TN} = \mathbb{E}_{\{\theta_A, \theta_B\}}[(p_B - h)(\theta_B + 1 - d_A^{TN})|Y_B] \end{cases}, \tag{4}$$

where $F(> 0)$ is the fixed investment cost of smart port development. Since scenario (N, T) is symmetric to scenario (T, N), we omit the derivation process to avoid redundancy.

In scenario (T, T), both θ_A and θ_B are visible, the indifferent point can be derived as $\tilde{x}^{TT} = \frac{1}{2} - \frac{\lambda(\theta_A-\theta_B)}{2(\lambda+K\gamma)} - \frac{K(p_A-p_B)}{2(\lambda+K\gamma)}$ and the payoff for each port is given by

$$\pi_i^{TT} = \mathbb{E}_{\theta_{-i}}\left[(p_i - h)\left(\theta_i + d_i^{TT}\right)|\theta_i\right] - F, \text{ where } i, -i = A, B. \tag{5}$$

For ease of comparison, we delegate payoffs for the two ports in four scenarios into the following Table 1.

Table 1. Payoffs for the two ports in four scenarios

port A (S_A)	port B (S_B) N	port B (S_B) T
N	$\pi_i^{NN} = \mathbb{E}_{\theta_i}[(p_i - h)(\theta_i + d_i^{NN})\|Y_i]$, where $d_i^{NN} = \frac{1}{2} - \frac{K(p_i - p_{-i})}{2(\lambda + K\gamma)}$, $i, -i = A, B$.	$\begin{cases} \pi_A^{NT} = \mathbb{E}_{\{\theta_A,\theta_B\}}[(p_A - h)(\theta_A + 1 - d_B^{NT})\|Y_A] \\ \pi_B^{NT} = (p_B - h)(\theta_B + d_B^{NT}) - F \end{cases}$, where $d_B^{NT} = \frac{1}{2} + \frac{\lambda(1-\rho)(\mu - \theta_B)}{2(\lambda + K\gamma)} - \frac{K(p_B - p_A)}{2(\lambda + K\gamma)}$.
T	$\begin{cases} \pi_A^{TN} = (p_A - h)(\theta_A + d_A^{TN}) - F \\ \pi_B^{TN} = \mathbb{E}_{\{\theta_A,\theta_B\}}[(p_B - h)(\theta_B + 1 - d_A^{TN})\|Y_B] \end{cases}$, where $d_A^{TN} = \frac{1}{2} + \frac{\lambda(1-\rho)(\mu - \theta_A)}{2(\lambda + K\gamma)} - \frac{K(p_A - p_B)}{2(\lambda + K\gamma)}$.	$\pi_i^{TT} = \mathbb{E}_{\theta_{-i}}[(p_i - h)(\theta_i + d_i^{TT})\|\theta_i] - F$, where $d_i^{TT} = \frac{1}{2} - \frac{\lambda(\theta_i - \theta_{-i})}{2(\lambda + K\gamma)} - \frac{K(p_i - p_{-i})}{2(\lambda + K\gamma)}$, $i, -i = A, B$.

Note that the two ports compete along two dimensions: (i) service price, and (ii) congestion information visibility. To formalize this interaction, we define the intensity of price competition faced by port i in scenario j as $|\, \partial d_i^j / \partial p_i \,|$, which measures the sensitivity of demand d_i^j to changes in port i's service price. Analogously, we define the intensity of congestion-driven competition as $|\, \partial d_i^j / \partial \theta_i \,|$, which captures the extent to which congestion information provided by port i affects the demand in scenario j.

Corollary 1. (Competitive dynamics of service price and congestion information)

(i) In all scenarios, price competition intensifies as port i's service capacity increases (i.e., $\frac{\partial}{\partial K}\left|\frac{\partial d_i^j}{\partial p_i}\right| > 0 \ \forall j \in \{NN, TN, NT, TT\}$);

(ii) If at least one port develops smart port, competition in congestion information weakens as service capacity increases (i.e., $\frac{\partial}{\partial K}\left|\frac{\partial d_i^j}{\partial \theta_i}\right| < 0 \ \forall j \in \{TN, NT, TT\}$);

(iii) When only one port develops smart port, competition in congestion information further weakens as the correlation of random parts ρ increases (i.e., $\frac{\partial}{\partial \rho}\left|\frac{\partial d_i^j}{\partial \theta_i}\right| < 0 \ \forall j \in \{TN, NT\}$).

Corollary 1 follows directly from the observation for d_i^j summarized in Table 1. As service capacity increases, the congestion disutility faced by port users diminishes. Consequently, port users become less sensitive to congestion and more responsive to price differences, rendering service price adjustments more effective. This intensifies price competition between the two ports.

By contrast, when at least one port develops smart port, congestion information becomes not salient in port users' decision-making. In this case, a tighter capacity constraint amplifies the role of congestion in port users' choices, thereby strengthening congestion-driven competition. Combining parts (i) and (ii) of Corollary 1 yields an important insight: as port capacities become more and more constrained, price competition softens while congestion-driven competition intensifies, a shift that fundamentally alters the strategic value of smart port development. This finding is consistent with industry observations. As the global shipping system has become increasingly congested, smart port initiatives have gained urgency: not only as tools for mitigating demand volatility, but also as instruments for reshaping co-opetition dynamics among ports (ESCAP 2021).

Part (iii) of Corollary 1 further shows that a higher correlation ρ attenuates the competitive impact of congestion information when only one port develops smart port. In scenarios (T, N) or (N, T), correlated demand implies that port users who access congestion information from the smart port can partially infer congestion conditions at the non-development port. As ρ increases, this informational spillover weakens the congestion-based differentiation advantage of the smart port, thereby eroding the strategic benefit of unilateral smart port development.

We solve the problems by backward induction. The equilibrium outcomes in each scenario are delegated to Appendix A1. The notations used in this paper are summarized in Table 2.

Table 2. The descriptions of notations.

Notations	Descriptions
θ_i	The random part of port i's demand, where $i \in \{A, B\}$ and $\theta_i \sim \mathcal{N}(\mu, \sigma^2)$
ρ	The correlation coefficient between θ_A and θ_B, i.e., $cov(\theta_A, \theta_B) = \rho$
Y_i	The signal of random part θ_i, where $i \in \{A, B\}$
t	The signal accuracy of Y_i if port i is not a smart port
S_i	The smart port development strategy of port i, where $i \in \{A, B\}$ and $S_i \in \{T, N\}$
λ	The port users' aversion to congestion
K	The service capacity of ports
$\mathcal{R}$	The information accuracy improvement through smart port development, where $\mathcal{R} = 1/(1 + t\sigma^2)$
γ	The port users' unit distance cost
h	The unit handling cost of port services in each port
F	The investment cost of the transition to a smart port
d_i	The deterministic part of port i's demand, where $i \in \{A, B\}$
D_i	The total demand of port i, where $i \in \{A, B\}$ and $D_i = \theta_i + d_i$
π_i	The posterior profit of port i, where $i \in \{A, B\}$

4. Analysis

4.1 Impact of Price and Data Visibility on Demand Volatility

Let $Var\,(D_i^j)$ denote the demand volatility faced by port i in scenario $j \in \{NN, TN, NT, TT\}$. The expected total congestion disutility of port users choosing port i's services, defined as the individual congestion disutility $(\lambda D_i^j)/K$ multiplied by aggregate demand D_i^j, can be written as

$$\mathbb{E}\left[\frac{\lambda D_i^j}{K} \cdot D_i^j\right] = \frac{\lambda}{K} \cdot \left\{Var\left(D_i^j\right) + \left(\mathbb{E}\left[D_i^j\right]\right)^2\right\}, \text{where } \mathbb{E}\left[D_i^j\right] = (2\mu + 1)/2, \quad (6)$$

which is monotonically increasing in the demand volatility $Var\left(D_i^j\right)$. Consequently, ports can reduce expected congestion disutility by mitigating demand volatility. We begin by examining the impact of two-dimensional competition (i.e., service pricing and congestion information) on demand volatility.

If port i does not develop smart port ($S_i = N$), port i's price responsiveness to demand information in scenario j is defined as $\partial\left(p_i^j\right)/\partial Y_i$. A positive price responsiveness (i.e., $\partial\left(p_i^j\right)/\partial Y_i > 0$) enables port i to set higher service prices during demand surges, which helps stabilize demand.

We first examine the impact of the price competition between two ports on their demand volatility when port i does not develop smart port see Lemma 1.

Lemma 1. Define $t_1 \doteq \frac{2(2\rho-1)}{\sigma^2[1-(2\rho-1)(1-\rho)]}$. The following results hold:

(i) If port i does not develop smart port ($S_i = N$), higher signal accuracy enables port i to adjust its service price more responsively to demand information (i.e., $\partial\left(p_i^{S_iS_{-i}}\right)/\partial Y_i > 0$ and $\partial\left\{\partial\left(p_i^{S_iS_{-i}}\right)/\partial Y_i\right\}/\partial t > 0$, $S_i = N$ and $S_{-i} \in \{T, N\}$);

(ii) In scenario (N,N), the demand volatility of port i decreases with signal accuracy (i.e., $\frac{\partial[Var(D_i^{NN})]}{\partial t} < 0,\ \forall i \in \{A,B\}$) when $\begin{cases} \rho \leq 1/2;\text{ or} \\ \rho > 1/2 \text{ and } t > t_1 \end{cases}$.

Lemma 1 (i) shows that a more accurate demand signal allows ports that do not develop smart ports to adjust service prices more aggressively. One might expect that, in scenario (N,N), a higher signal accuracy would help ports mitigate demand volatility through more responsive pricing. Lemma 1 (ii) reveals that this intuition holds only when the correlation of random parts is sufficiently low (i.e., $\rho \leq 1/2$). When the correlation is high ($\rho > 1/2$), however, a more accurate signal will exacerbate demand volatility when signal accuracy is insufficient (i.e., $\frac{\partial[Var(D_i^{NN})]}{\partial t} > 0\ \ \forall t < t_1$).

This finding constitutes the *signal level* mechanism of the smart trap. Improving demand information accuracy may backfire when the correlation of demand random parts is high and signal precision remains insufficient. Under moderate correlation, a more precise signal does not simply reduce noise; it may also magnify the perceived congestion disutility of port users across ports, making demand allocation more volatile.

To understand this result, we consider two special cases. First, when $\rho = 0$, each port adjusts its service price in response to its own demand realization without materially affecting the rival's pricing decision. As a result, higher signal accuracy unambiguously improves the ability of both ports to stabilize demand through responsive pricing. In contrast, when $\rho = 1$, price adjustments by the two ports then move in the same direction: both ports raise (lower) prices when demand is expected to be high (low). Under such circumstances, the effectiveness of joint price adjustments in stabilizing demand depends primarily on the precision of the demand information. When no useful information is available ($t = 0$), price decisions are based on prior expectations $\mathbb{E}[\theta_i] = \mu$. As signal accuracy increases, ports place greater weight on demand signals when forming demand expectations (i.e., $\frac{\partial}{\partial t}\left\{\frac{\partial \mathbb{E}[\theta_i|Y_i]}{\partial Y_i}\right\} > 0$), which may exacerbate the mismatch between demand and price decisions. If signal accuracy remains insufficient ($t < t_1$), such a mismatch caused by unreliable demand information dominates, leading to higher demand volatility.

Then, we examine the conditions under which smart port development can mitigate demand volatility. Since ports A and B are symmetric, we focus on port A and refer to port B as the rival.

Proposition 1. Define $\rho_1 \doteq \frac{2\sqrt{63\lambda^2+120\lambda K\gamma+64K^2\gamma^2}-4(3\lambda+2\gamma K)}{3(3\lambda+4\gamma K)}$. The following results hold:

(i) In scenario (T, N), the demand volatility of port A (resp., the rival) decreases (resp., increases) with the information accuracy improvement (i.e., $\frac{\partial[Var(D_A^{TN})]}{\partial \mathcal{R}} < 0$ and $\frac{\partial[Var(D_B^{TN})]}{\partial \mathcal{R}} > 0$);

(ii) When the rival adopts the strategy $S_B = N$, port A can reduce its demand volatility by developing smart port (i.e., $Var(D_A^{TN}) < Var(D_A^{NN})$). This mitigation effect amplifies with the information accuracy improvement (i.e., $\frac{\partial\{Var(D_A^{NN})-Var(D_A^{TN})\}}{\partial \mathcal{R}} > 0$);

(iii) When the rival adopts the strategy $S_B = T$, port A can reduce its demand volatility by developing smart port (i.e., $Var(D_A^{TT}) < Var(D_A^{NT})$) when $\rho < \rho_1$; Otherwise ($\rho \geq \rho_1$), there exist a threshold $\mathcal{R}_1$ such that $Var(D_A^{TT}) < (>)\, Var(D_A^{NT})$ when $\mathcal{R} > (<)\mathcal{R}_1$;

(iv) The threshold ρ_1 increases with service capacity while the threshold $\mathcal{R}_1$ decreases with service capacity (i.e., $\frac{\partial \rho_1}{\partial K} > 0$ and $\frac{\partial \mathcal{R}_1}{\partial K} < 0$).

In scenario (T, N), by developing smart port ($S_A = T$), the information accuracy improvement enhances the port A's ability to adjust its service price to mitigate demand volatility. In contrast, port B's information disadvantage by adopting $S_B = N$ makes its price less responsive to demand signal and thus more difficult to mitigate demand volatility. As such, Proposition 1 (i) shows that in scenario (T, N), the port A's demand volatility decreases with demand information accuracy improvement, while its rival suffers the opposite effect.

Proposition 1 (ii) confirms that when the rival does not invest in smart port ($S_B = N$), developing smart port allows port A to better stabilize demand, particularly when demand accuracy improvement is significant. However, Proposition 1 (iii) highlights that this intuition does not always extend to the situation where the rival also develops smart port. When correlation of demand random parts is sufficiently high ($\rho > \rho_1$), switching from $S_A = N$ to $S_A = T$ may actually increase demand volatility when signal accuracy improvement is insufficient (i.e., $\mathcal{R} < \mathcal{R}_1$). We note that two forces jointly drive this result. On the one hand, as the correlation ρ increases in scenario (N, T), port B's congestion-driven competitive advantage is weakened (cf. Corollary 1). On the other hand, even if port A does not develop smart port, it can still set a responsive service price and thus effectively mitigate demand volatility (cf. Lemma 1). Consequently, when the correlation is moderate and demand accuracy improvement is insufficient (see Figure 3), port A can achieve lower demand volatility by not developing smart port.

This result represents the *market-outcome level* mechanism of the smart trap, which is distinct from the *signal level* distortion identified in Lemma 1. While Lemma 1 shows that more precise signals may amplify the volatility of perceived congestion disutility of port users, Proposition 1(iii) suggests that this distortion still exist and can be reinforced by the equilibrium adjustment of service prices and port users' substitution behavior. In other words, the *signal* *level* volatility amplification will not be mitigated through competitive pricing; instead, it may even transmit into demand volatility in *market-outcome level*, causing ports to avoid developing smart port to prevent intensified congestion-driven competition from exacerbating demand volatility.

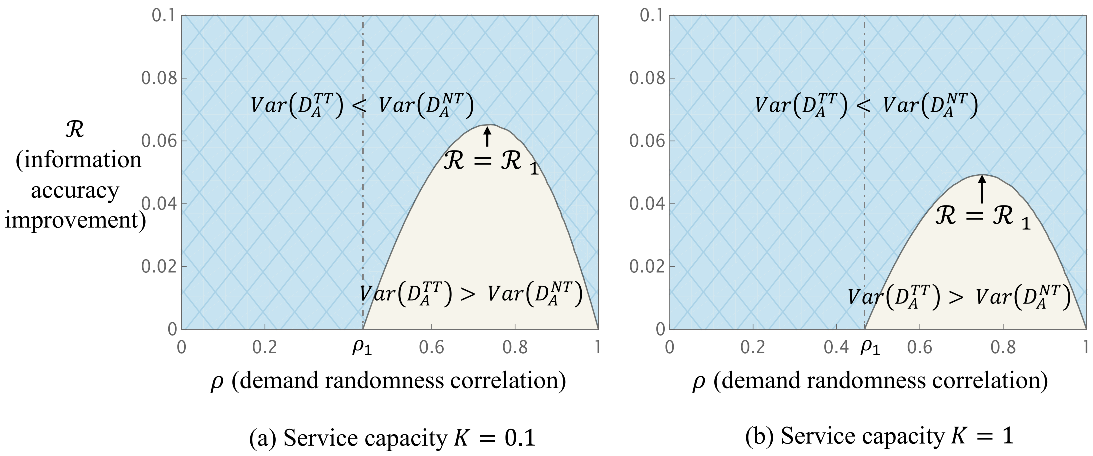


Figure 3. The impact of correlation and information accuracy improvement on port A's demand volatility ($\gamma = 0.2,\ \sigma = 1,\ \lambda = 1$).

Proposition 1 (iv) further shows that as port service capacity increases, the regions where smart port development amplifies demand volatility will shrink (cf. panels (a) and (b) in Figure 3). This finding suggests that, amid growing port congestion impact, investments in smart port should be complemented by improvements in service capacity. This helps enhance demand information that translates into effective congestion mitigation rather than excessive traffic volatility.

Interestingly, the threshold $\mathcal{R}_1$ is non-monotonic in ρ: it first increases and then decreases with ρ (see Figure 3). The underlying mechanism is that the moderate correlation of demand random part simultaneously weakens the rival's data visibility advantage in scenario (N,T) while intensifying price competition, thereby reducing the effectiveness of service prices in stabilizing demand. To see this more clearly, consider the extreme case $\rho = 1$. Since $\theta_A = \theta_B$ holds, congestion-driven competition is eliminated in both scenarios (N, T) and (T, T). In such situation, smart port development will be useful in for mitigating demand volatility by improving information accuracy.

4.2 Equilibrium Smart Port Development Strategy

In this section, we first derive the equilibrium smart port development strategy when there is no smart port development cost (i.e., $F = 0$). This helps provide clearer insights for decision-makers and stakeholders in port operations.

Lemma 2. Given $F = 0$, there are thresholds $\mathcal{R}_2$ and $\mathcal{R}_3 \geq (\mathcal{R}_2)$ such that

(i) When $\mathcal{R} > \mathcal{R}_3$, port A is better off choosing $S_A = T$ than $S_A = N$ regardless of the rival's strategy S_B (i.e., $\mathbb{E}\left[\pi_A^{TS_B}\right] > \mathbb{E}\left[\pi_A^{NS_B}\right]$ $\forall S_B \in \{T, N\}$);

(ii) When $\mathcal{R} < \mathcal{R}_2$, port A is better off choosing $S_A = N$ than $S_A = T$ regardless of the rival's strategy S_B (i.e., $\mathbb{E}\left[\pi_A^{TS_B}\right] < \mathbb{E}\left[\pi_A^{NS_B}\right]$ $\forall S_B \in \{T, N\}$);

(iii) Both $\mathcal{R}_2$ and $\mathcal{R}_3$ decreases with ρ (i.e., $\frac{\partial \mathcal{R}_2}{\partial \rho} < 0$ and $\frac{\partial \mathcal{R}_3}{\partial \rho} < 0$).

We note that with sufficient improvement in information accuracy, smart port development will play an important role in determining a more responsive price and mitigating demand volatility, leading to a higher profitability. As such, Lemma 2 (i) shows that a significant improvement in information accuracy (i.e., $\mathcal{R} > \mathcal{R}_3$) will incentivize smart port development. In contrast, Lemma 2 (ii) shows that when the improvement in information accuracy is very limited (i.e., $\mathcal{R} < \mathcal{R}_2$), port A can be better off without smart port development. This finding provides additional justification for not developing smart port beyond concerns about demand volatility (cf. Proposition 1 (iii)). In other words, when facing two-dimensional competition, a port can potentially achieve a higher profit while avoiding the amplified demand volatility by not developing smart port.

Further, an increase in the coefficient ρ will raise the threshold of information accuracy improvement that determines port A's smart port development decisions (Lemma 2 (iii)). Recall Corollary 1 (iii) that an increase in ρ will alleviate the congestion-driven competition, allowing for higher profit margins from responsive price decisions through smart port development. As such, the region of information accuracy improvement in favor of smart port increases (i.e., $\mathcal{R} > \mathcal{R}_3$ with $\frac{\partial \mathcal{R}_3}{\partial \rho} < 0$), while the region that is unfavorable to smart port decreases (i.e., $\mathcal{R} < \mathcal{R}_2$ with $\frac{\partial \mathcal{R}_2}{\partial \rho} < 0$).

We note that when $\mathcal{R}_2 < \mathcal{R} < \mathcal{R}_3$, there is no dominant strategy for port A. In this case, the optimal strategy of port A's strategy is affected by its rival's choices. Hence, we examine the equilibrium strategy matrix for the two ports in Proposition 2.

Proposition 2. (The equilibrium strategy matrix for the two ports)

(i) (T, T) is the equilibrium strategy if $\mathcal{R} > \mathcal{R}_3$;

(ii) (N, N) is the equilibrium strategy if $\mathcal{R} < \mathcal{R}_2$;

(iii) (T, N) or (N, T) is the equilibrium strategy if $0 < \rho < 1$ and $\mathcal{R}_2 < \mathcal{R} < \mathcal{R}_3$.

Proposition 2 (i) and (ii) follow directly from the results in Lemma 2 (i.e., $\forall i \in \{A, B\}$, $S_i = N$ when $\mathcal{R} < \mathcal{R}_2$; $S_i = T$ when $\mathcal{R} > \mathcal{R}_3$). Proposition 2 (iii) suggests that when the information accuracy improvement is moderate, either scenarios (T, N) or (N, T) could be an equilibrium for two ports (see Figure 4 as a visual illustration). When the rival chooses $S_B = N$, the switching of port A's strategy from $S_A = N$ to $S_A = T$ benefits both ports. On the one hand, port A can still benefit from moderate information accuracy improvement (i.e., $\mathcal{R}_2 < \mathcal{R} < \mathcal{R}_3$). On the other hand, the rival also benefits from mitigated price competition as port A will attract port users through the congestion-driven competition. Therefore, (T, N) could be an equilibrium, and a symmetric analysis indicates that (N, T) is also an equilibrium. The existence of asymmetric equilibria suggests that uniform technology mandates may be suboptimal. Instead, phased or differentiated policy interventions may achieve superior governance outcomes.

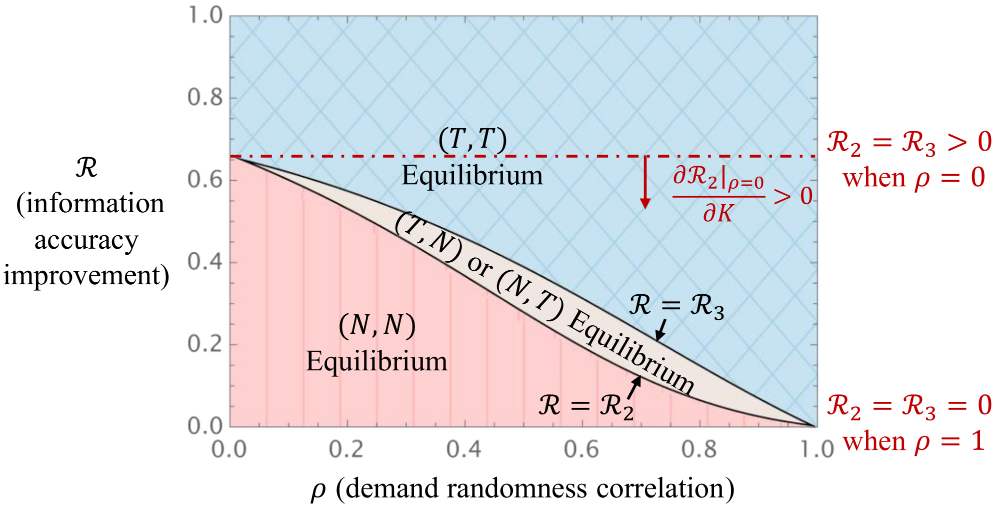


Figure 4. The equilibrium strategy matrix for two ports ($\gamma = 1,\ \sigma = 1,\ \lambda = 1,\ K = 0.2,$ $F = 0$).

Intriguingly, when either $\rho = 0$ or $\rho = 1$, we find that $\mathcal{R}_2 = \mathcal{R}_3$ such that (N, T) or (T, N) will be eliminated (see Figure 4). In contrast, when ρ is moderate, the gap between thresholds $\mathcal{R}_2$ and $\mathcal{R}_3$ is more pronounced, making asymmetric equilibrium more likely to emerge. This finding can be well explained by Lemma 2. That is, an increase in ρ can mitigate congestion-driven competition such that the port chooses $S_i = N$ benefits more from port users' congestion disutility reduction while the port chooses $S_{-i} = T$ benefits more from responsive price decisions. However, with ρ further increases, both ports will choose $S_i = T$

as their dominant strategies to focus on congestion-driven competition (cf. Lemma 2(iii)). It follows that ports' equilibrium strategies change from $(N, T)/(T, N)$ to (T, T).

It is worth noting that $\mathcal{R}_2|_{\rho=0}$ (i.e., the value of $\mathcal{R}_2$ when $\rho = 0$) increases with the service capacity K (i.e., $\frac{\partial \mathcal{R}_2|_{\rho=0}}{\partial K} > 0$). In other words, an increase in service capacity can change ports' equilibrium strategy from (N, N) to $(N, T)/(T, N)$ or from $(N, T)/(T, N)$ to (T, T). This is because price competition intensifies while congestion-driven competition weakens (Corollary 1 (i)). So the ports gain from softened congestion-driven competition by developing smart port.

However, when neither port develops smart port, the two ports solely compete on service prices. This eliminates the benefits gained from information accuracy improvement and may lead to Prisoner's Dilemma shown in Corollary 2.

Corollary 2. (Prisoner's Dilemma analysis**)** In the region of (N, N) equilibrium, there exist thresholds ρ_2 and $\mathcal{R}_4 (< \mathcal{R}_2)$ such that $\mathbb{E}[\pi_i^{TT}] > \mathbb{E}[\pi_i^{NN}]$ when $\rho < \rho_2$ and $\mathcal{R} > \mathcal{R}_4$.

Corollary 2 suggests that when competing ports fail to coordinate on smart port development, the result of individual rational choices (i.e., (N, N) equilibrium) not only harms port profitability but also creates systemic inefficiencies for port traffic system (see Figure 5 as a visual illustration). This finding highlights the need for coordinated efforts or regulatory interventions to overcome potential impediments to port digitization, as the Swedish Maritime Administration has done with competitive ports in a joint program to improve port efficiency by engaging together in smart port development rather than isolated infrastructure upgrades (Sjöfartsverket, 2021). To such Prisoner's Dilemma, ports can alleviate public anxiety about congestion or improve their service capacity, thereby mitigating congestion disutility and achieving (T,T) equilibrium (cf. Proposition 2).

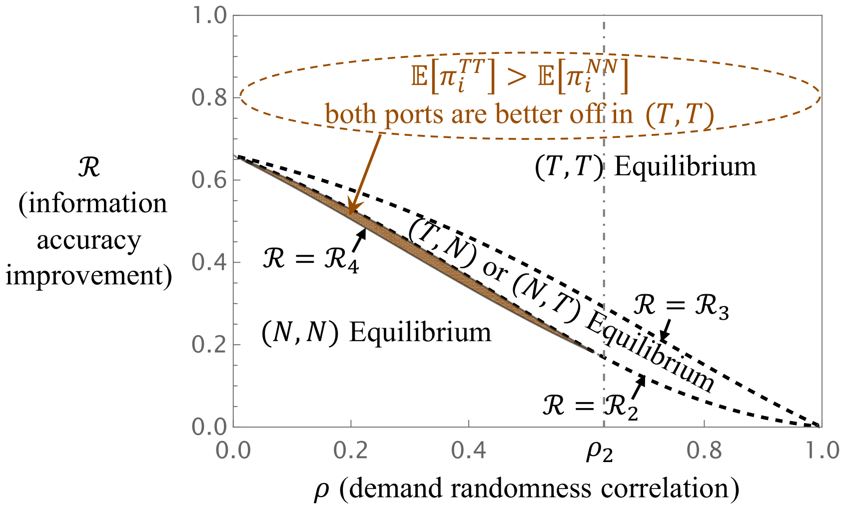


Figure 5. The Prisoner's Dilemma when neither port develops smart port ($\gamma = 1,\ \sigma = 1,$ $\lambda = 1,\ K = 0.2,\ F = 0$).

It is worth noting that this Prisoner's Dilemma represents the *strategic-adoption level* consequence of the smart trap, and it is structurally different from the signal level (Lemma 1) and market-outcome level (Proposition 1(iii)) mechanisms discussed earlier. While those two mechanisms concern the consequences of smart port development (i.e., how information accuracy and competitive pricing interact to amplify demand volatility), the Prisoner's Dilemma concerns the smart port development decision itself. In other words, each port's anticipation of the demand volatility amplification (from the signal and market levels) distorts its private development incentives, resulting in a coordination failure in which neither port invests despite joint smart port developments being Pareto-improving. In this sense, the "smart trap" paradox operates like a casual chain: signal level distortion (Lemma 1) propagates into market-outcome level demand volatility (Proposition 1(iii)), which in turn distorts smart port development incentives and leads to the Prisoner's Dilemma.

Then, we examine the impact of smart port development cost on the equilibrium strategy matrix for the two ports.

Proposition 3. (The impact of smart port development cost) There are two thresholds F_1 and F_2 such that

(i) (T, T) is the equilibrium strategy if $\mathcal{R} > \mathcal{R}_3$ and $F < F_2$;

(ii) (N, N) is the equilibrium strategy if $\mathcal{R} < \mathcal{R}_2$, or $\mathcal{R} > \mathcal{R}_2$ and $F > F_1$;

(iii) (T, N) or (N, T) is the equilibrium strategy if $\mathcal{R}_2 < \mathcal{R} < \mathcal{R}_5$ and $\max\{0, F_2\} < F < F_1$.

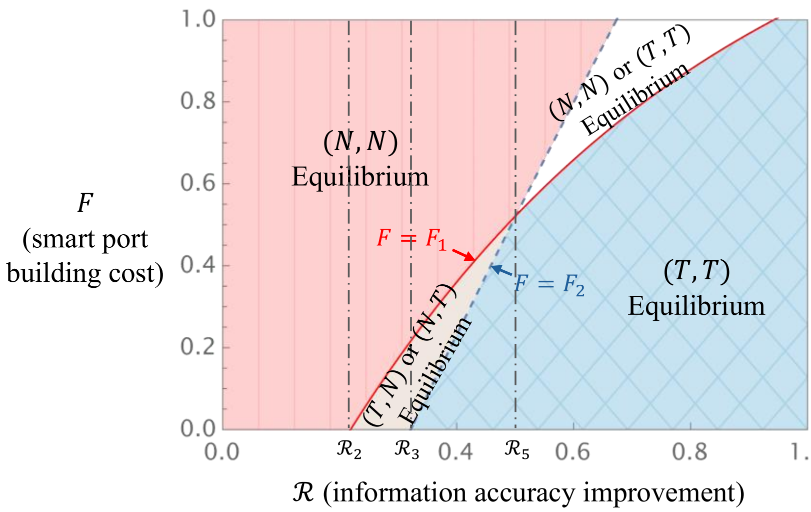


Figure 6. The impact of smart port development cost on the equilibrium strategy matrix for two ports ($\gamma = 1,\ \sigma = 1,\ \lambda = 1,\ \rho = 0.5,\ K = 0.5$).

Intuitively, a low development cost favors (T, T) equilibrium (Proposition 3 (i)) while a sufficiently high development cost favors (N, N) equilibrium (Proposition 3 (ii)). In contrast, asymmetric $(N, T)/(T, N)$ equilibrium occurs when the development cost is moderate

(Proposition 3 (ii)). Interestingly, we show that (N, N) and (T, T) equilibrium will coexist when information accuracy improvement $\mathcal{R}$ is high and development cost F is moderate (see Figure 6). The rationale behind this finding is explained as follows. When $\mathcal{R}$ is low, the improvement in information accuracy by smart port development will be significant, which favors more responsive pricing and more profitable port operations. If the development cost is low ($F \leq F_1$), then there is only (T, T) equilibrium. However, once $F_1 < F < F_2$ and the development cost becomes non-negligible, there is a mixed equilibrium between (T, T) and (N, N). We note that in the (N, N) equilibrium, there is no congestion-driven competition due to a lack of data visibility (see Corollary 1). As such, if $S_i = S_{-i} = N$ are chosen, both ports will suffer from limited demand information accuracy, but the high development cost and losses from congestion-driven competition can be avoided. So, (N, N) may also arise as an equilibrium.

4.3 Win-win Opportunities

In section 4.1 and section 4.2, we study the impact of smart port development on mitigating ports' demand volatility and improving ports' profits separately. As shown in section 4.1, greater demand volatility translates to higher congestion disutility borne by port users. One natural question is: for ports developing smart port, is there a win-win opportunity to simultaneously mitigate overall demand volatility and enhance profitability? To address this question, we combine the findings from Propositions 1 and 3 to derive the following Corollary.

Corollary 3. (The win-win opportunities of smart port development)

(i) In the (T,T) equilibrium, each port's demand volatility is lower than when it does not develop smart port (i.e., $Var(D_i^{TT}) < Var(D_i^{NT})$ when $\mathbb{E}[\pi_i^{TS_{-i}}] > \mathbb{E}[\pi_i^{NS_{-i}}]$ $\forall S_{-i} \in \{T,N\}$);

(ii) In the (N,N) equilibrium, each port's demand volatility is higher than when it develop smart port (i.e., $Var(D_i^{NN}) > Var(D_i^{TN})$ when $\mathbb{E}[\pi_i^{NS_{-i}}] > \mathbb{E}[\pi_i^{TS_{-i}}]$ $\forall S_{-i} \in \{T,N\}$);

(iii) In $(T,N)/(N,T)$ equilibrium, the demand volatility of the port with smart port development may either increase or decrease because of its smart port development.

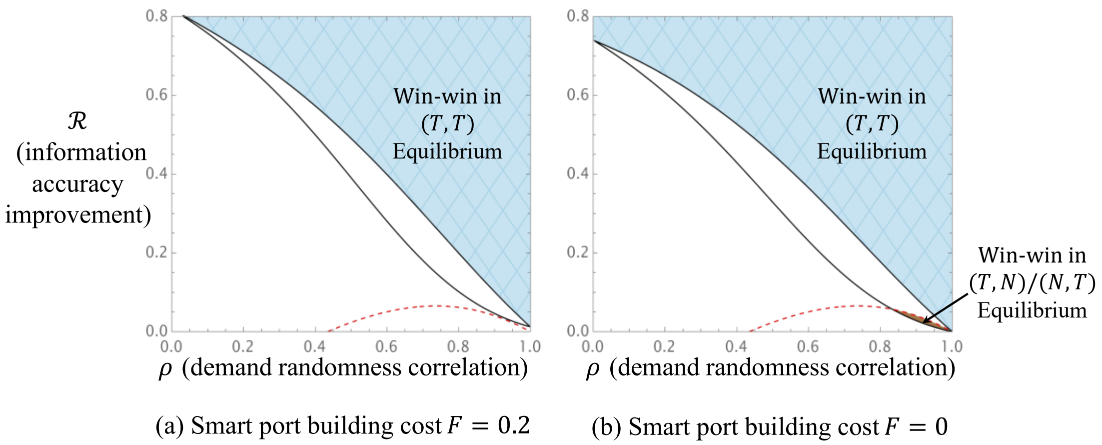


Figure 7. The impact of smart port development cost on the equilibrium strategy matrix ($\gamma = 0.1,\ \sigma = 1,\ \lambda = 1,\ \rho = 1/2,\ K = 0.2$).

Corollary 3 (i) suggests that the demand volatility can be effectively mitigated in the (T,T) equilibrium. Therefore, policies encouraging smart port development such as investment subsidies can effectively reduce congestion disutility for port users and achieve a win-win situation. From the perspective of port operators, enhancing service capacity also facilitates the achievement of (T,T) equilibrium, thereby benefiting port users (cf. Proposition 2). In contrast, the (N,N) equilibrium benefits only ports themselves in dual-dimensional competition, while port users suffer from reduced data visibility and higher congestion disutility. Therefore, Corollary 3 (ii) shows that there is no win-win opportunity in the (N, N) equilibrium.

Corollary 3 (iii) reveals win-win opportunities exist in asymmetric equilibrium. However, such opportunity highly depends on smart port development cost F and demand randomness correlation ρ. As shown in Figure 7, if the development cost is relatively high (panel (a)), no win-win opportunity exists in the $(T, N)/(N, T)$ equilibrium. However, once the development cost becomes sufficiently low, both port users and the port developing smart port will benefit from reduced demand volatility when ρ is high. This is because a large demand randomness correlation ρ mitigates congestion-driven competition, enabling ports to more effectively adjust price decisions to alleviate demand volatility (cf. Proposition 1). It follows that port users can also benefit from reduced congestion disutility, thereby achieving a win-win situation. This finding holds significant implications, as the likelihood of random shocks occurring among ports is increasing. Therefore, port operators and policymakers should dynamically adjust their in responses to changing conditions to incentivize smart port development while ensuring that the interests of port users are not compromised.

4.4 Environmental Performance Analysis

In Sections 4.1-4.2, we show that smart port development reshapes demand allocations through service pricing responsiveness and congestion information visibility. These demand reallocations directly alter port congestion levels. Crucially, port congestion is not merely an operational inefficiency but a significant source of environmental externalities. Vessel queuing at anchorage, engine idling at berth, and suboptimal traffic routing all generate excess emissions that scale with congestion severity (Li et al. 2024; Wang et al. 2024a). During the 2021 Los Angeles-Long Beach congestion crisis, anchored vessels produced over 100 tons of pollutants daily (Lind et al. 2022; Vukić and Lai 2022). Because the same equilibrium demand allocations that determine ports' profitability also determine their congestion levels, every competitive result derived in Sections 4.1-4.3 carries a direct and traceable environmental consequence. The environmental analysis below is therefore not a separate module but an alternative reading of the same equilibrium.

Following Li et al. (2024) and Niu et al. (2024c), we examine the environmental performance by employing the environmental impact (EI) index, which is useful in mapping the port congestion level to the environmental externalities. Let $\alpha(>0)$ denote baseline environmental impact of serving a unit number of port users, and $\beta(>0)$ denote the additional environmental impact due to port congestion. It follows that in scenario j, the environmental impact arising from port i serving D_i users under congestion likelihood $\frac{D_i^j}{K}$ can be calculated by $\left(\alpha+\beta\frac{D_i^j}{K}\right)D_i$. So, the EI index can be formulated as follows

$$EI^j=\mathbb{E}\left[\sum_{i\in\{A,B\}}\left\{\left(\alpha+\beta\frac{D_i^j}{K}\right)D_i\right\}\right],\text{ where } j\in\{TT,NT,TN,NN\}. \tag{7}$$

In scenario j, substituting the equilibrium quantities into the EI index yields the results summarized in Table 3.

Table 3. The Environmental Impact in each scenario

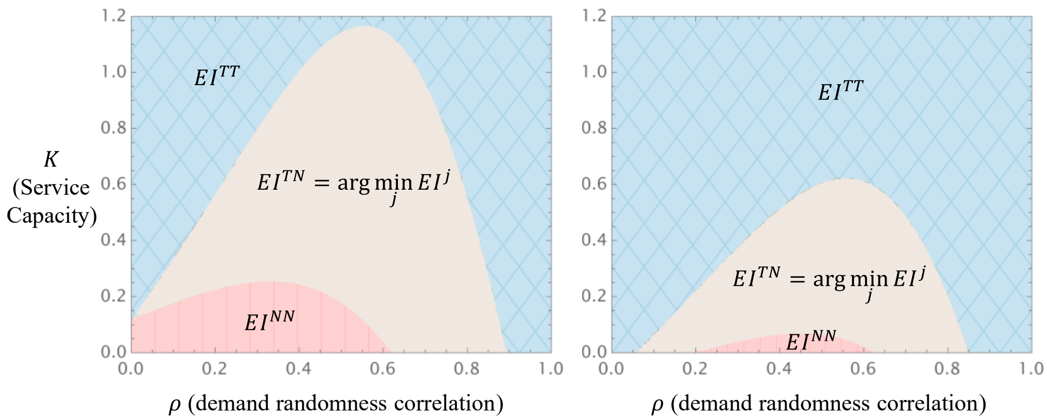
Strategy matrix	EI^j
(N,N)	$\alpha(1+2\mu)+\frac{(1+2\mu)^2\beta}{2K}+\frac{4\beta\sigma^2\{4+t\sigma^2[6+t(2-\rho^2)\sigma^2]\}}{2K[2-t(2-\rho)\sigma^2]^2}$
$(T,N)/(N,T)$	$\alpha(1+2\mu)+\frac{4\beta\mu(1+\mu)}{2K}+\frac{\beta\mathcal{H}_1}{2K(\lambda+K\gamma)^2(-4+t(-4+\rho^2)\sigma^2)^2}$
(T,T)	$\alpha(1+2\mu)+\frac{(1+2\mu)^2\beta}{2K}+\frac{2\sigma^2\beta[\lambda^2(5+\rho-4\rho^2)+2K\lambda\gamma(4+\rho-3\rho^2)+2K^2\gamma^2(2-\rho^2)]}{2K(\lambda+K\gamma)^2(2-\rho)^2}$

Note $\mathcal{H}_1=K^2\gamma^2\{16+8\sigma^2[6+4\rho+t(4-\rho^2)]+t\sigma^4[8(10-\rho^3)+4(16-\rho)\rho-t(4-\rho^2)^2]+4t^2(2+\rho)^2(2-\rho^2)\sigma^6\}+2K\lambda\gamma\{16+8\sigma^2[(6-\rho)(1+\rho)+t(4-\rho^2)]+t\sigma^4[2(4-\rho)(1+\rho)(10+2\rho-\rho^2)-t(4-\rho^2)^2]+t^2(2+\rho)^2(8+\rho-6\rho^2+\rho^3)\sigma^6\}+\lambda^2\{16+4\sigma^2[13+8t+10\rho-(3+2t)\rho^2]+t\sigma^4[t(4-\rho^2)^2+(1+\rho)(88-\rho(16+7\rho-\rho^2))]+t^2\sigma^6\rho(1+\rho)[36-(4-\rho)(1+\rho)(1+2\rho)]\}$.

Proposition 4. When neither port develops smart ports, the environmental impact is less than that when joint smart port developments (i.e., $EI^{NN}<EI^{TT}$) if $\max\{0,\rho_{EI1}\}<\rho<\rho_{EI2}$ and $K<K_{EI1}$.

Proposition 4 shows that the smart port development does not necessarily mitigate the environmental impact due to port congestion. When ports' service capacities are high ($K\geq K_{EI1}$), joint smart port developments can indeed mitigate environmental impacts. Note that port users' service choices are very sensitive to the service price adjustment of ports under a high service capacity (cf. Corollary 1(i)). It follows that smart port development enables both ports to determine service prices more responsively to demand information, thereby avoiding extreme congestion and mitigating the associated environmental impact.

In contrast, when ports' service capacities are insufficient ($K<K_{EI1}$), joint smart port developments can alleviate environmental impact only when the correlation ρ is either sufficiently high or low (i.e., $\rho>\rho_{EI2}$ or $\rho<\max\{0,\rho_{EI1}\}$). When the correlation is sufficiently high ($\rho > \rho_{EI2}$), severe congestion at both ports is more likely to occur. In such situations, the decision-making bias arising from inaccurate congestion information may further amplify congestion impacts and harm the environment. So, joint smart port developments become important to alleviate environmental impacts. In contrast, when the correlation of demand random part is sufficiently low ($\rho < \max\{0, \rho_{EI1}\}$), the two ports are unlikely to experience severe congestion simultaneously. Consequently, joint smart port developments become highly effective in alleviating environmental impact during surge-demand periods, as port users can select ports with lower congestion levels upon observing congestion information. However, when $\max\{0, \rho_{EI1}\} < \rho < \rho_{EI2}$, joint smart port developments cannot alleviate environmental impact as each port is less likely to benefit from demand allocation flexibility.



(a) Information accuracy improvement ($\mathcal{R} = 0.2$) (b) Information accuracy improvement ($\mathcal{R} = 0.3$)

Figure 8. The impact of smart port development cost on the equilibrium strategy matrix for two ports ($\gamma = 1,\ \sigma = 1,\ \lambda = 1,\ \alpha = \beta = 1$).

We further conduct extensive numerical studies to investigate port decisions that achieve minimal environmental impact (see Figure 8). We find that with service capacity increases, the scenario leading to minimal environmental impact gradually shifted from (N, N) to

$(T,N)/(N,T)$, ultimately evolving into (T,T). That is, service capacity of ports plays a pivotal role in determining how environmental externalities benefit from smart port development. In addition, Figure 8 also indicates that greater information accuracy improvement can further expand the region where smart port development alleviates the environmental impact. This outcome underscores the urgent need to expand service capacity or further enhance information accuracy when considering the environmental impact when developing smart ports.

5. Empirical Illustration

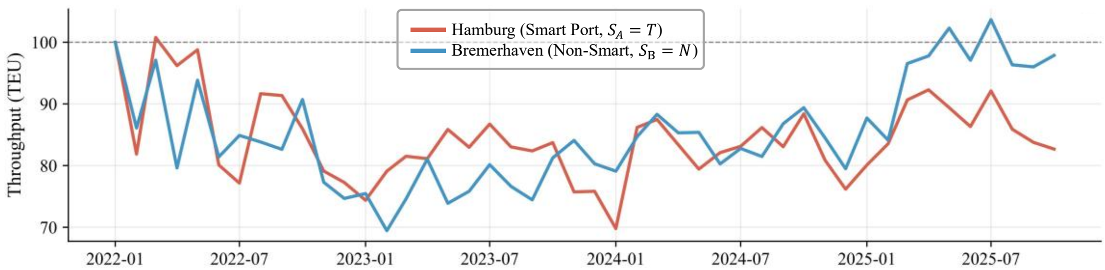


Figure 9. Monthly throughput da1ta of two ports from January 2022 to October 2025.

We apply the model to a real-world port pair to examine how the theoretical predictions align with observed behavior. The Port of Hamburg and the Port of Bremerhaven are Germany's two largest container ports, located approximately 120 km apart and serving overlapping North Sea hinterland demand. Hamburg has maintained a fully operational smart port infrastructure since 2014, leveraging real-time vessel tracking, AI-assisted berth planning, and open congestion dashboards (Offshore Energy 2014). Bremerhaven, by contrast, operated under a traditional information management regime throughout our sample period, only initiating a formal SmartPort transition strategy in April 2025 (Bremen Ports 2025). This persistent asymmetry directly mirrors the (T,N) equilibrium studied in our model. We use monthly throughput data (unit: TEU) for both ports from January 2022 to October 2025, sourced from the German Federal Statistical Office (GENESIS-Online 2026). The throughput series are depicted in Figure 9.

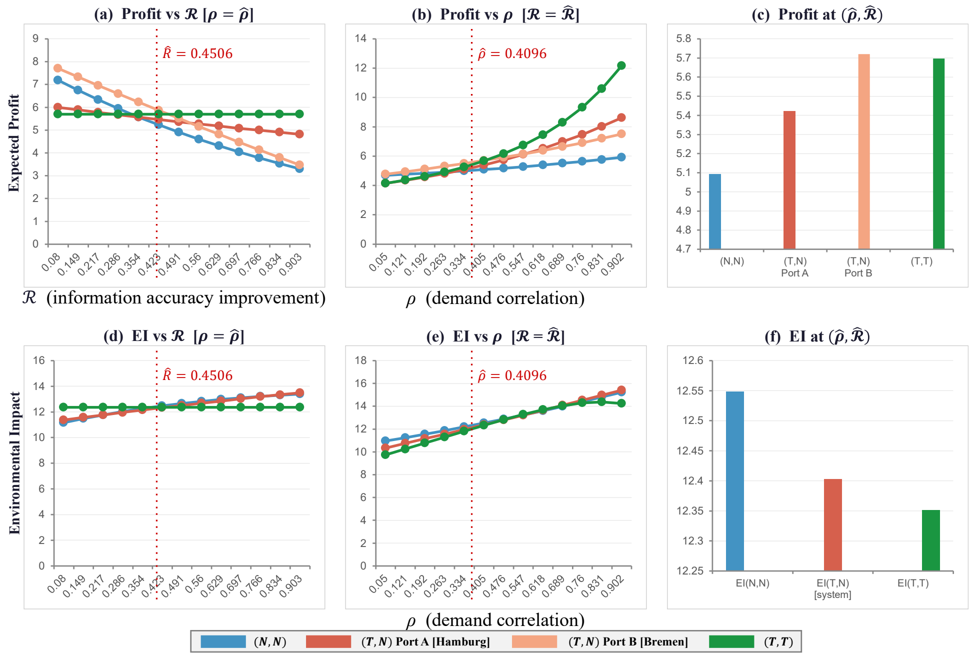


Figure 10. The profits and EI indexes ($\gamma = 1,\ \sigma = 1,\ \lambda = 5,\ K = 1,\ \mu = 0$).

Parameter calibration. We apply ARIMA models to the log-transformed throughput series to extract the stochastic demand component θ_i. The optimal specifications, selected by minimizing the AIC criterion, are ARIMA(0,0,2) for Hamburg and ARIMA(2,0,0) for Bremerhaven. The ARIMA residuals serve as proxies for the demand shock θ_i. Each specification includes an intercept term, which is $\mu^H = -0.0012$ or $\mu^B = -0.0031$. We therefore normalize $\mu = 0$ without loss of generality in the following numerical analysis. We estimate the pooled demand variance as $\hat{\sigma}^2 = 0.0049$ and the correlation coefficient between the two ports' residuals as $\hat{\rho} = 0.3462$ (p-value = 0.0047 < 0.05), consistent with their shared exposure to North Sea trade cycles. We estimate the information accuracy improvement $\hat{\mathcal{R}}$

using the in-sample R^2 of the ARIMA model fitted to Bremerhaven's series. The fraction of unexplained variance, 45.06%, represents the genuine uncertainty that smart port development would additionally resolve, yielding $\hat{\mathcal{R}} = 0.4506$. Environmental impact coefficients are calibrated using industry benchmarks from VesselBot (2024), yielding $\alpha = 4.74$ and $\beta = 0.29$. The resulting profit levels and environmental impact indices are presented in Figure 10.

Finding 1: The smart trap. Hamburg's log-demand residual variance is slightly higher than Bremerhaven's ($\mathrm{Var}_{Hamburg}^{TN}/\mathrm{Var}_{Bremerhaven}^{TN} = 1.1395 > 1$). This appears paradoxical because smart port development is meant to stabilize demand. However, this is precisely the smart trap mechanism identified in Proposition 1(iii). In this case, $\hat{\rho}$ is moderate and $\hat{\mathcal{R}}$ sits below the critical threshold, placing the system squarely in the smart trap region where unilateral development increases the developer's own demand volatility.

Finding 2: The asymmetric equilibrium. The calibrated parameter pair $(\hat{\rho}, \hat{\mathcal{R}})$ falls within the asymmetric equilibrium region of Proposition 2 (see Figure 11), consistent with the persistent decade-long asymmetry between the two ports. Moreover, the parameter pair lies in close proximity to the (T, T) boundary. Two converging pressures appear to have shifted the competitive calculus recently. Congestion at Bremerhaven intensified sharply, with berth waiting times surging by 77% between April and May 2025 (Cooperative Logistics Network 2025). As demand uncertainty becomes more consequential for congestion allocation, the relative payoff of acquiring real-time demand signals grows. This is consistent with Proposition 2: as the information accuracy improvement increases, the (T, N) equilibrium loses attractiveness and (T, T) tends to emerge, aligning with Bremerhaven's smart port development in 2025.

Finding 3: Environmental improvement. At the calibrated parameters, we obtain $EI^{NN} > EI^{TN} > EI^{TT}$. Smart port development reduces system-wide emissions, with each step toward fuller development yielding further environmental improvement. Even unilateral development in the (T, N) equilibrium already delivers measurable environmental gains relative to the (N, N) baseline, despite the concurrent smart trap effect on demand volatility. The ordering further shows that moving from (T, N) to full joint development yields additional environmental benefits, providing an environmental rationale for Bremerhaven's transition.

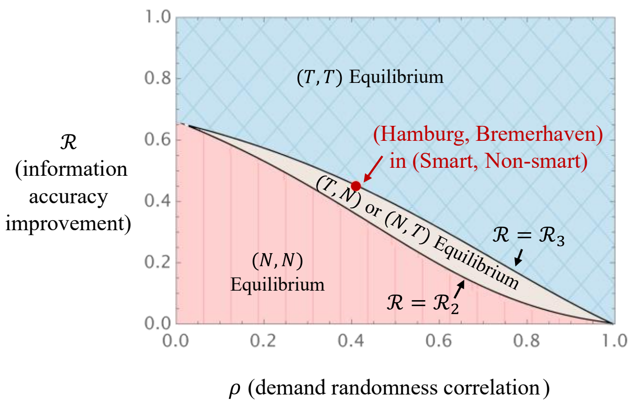


Figure 11. Equilibrium regions of two ports ($\gamma = 1,\ \sigma = 1,\ \lambda = 5,\ K = 1,\ \mu = 0$).

6. Conclusion

This study investigates the strategic implications of smart port in competitive port systems subject to demand randomness and congestion constraints. While smart port initiatives are often promoted as a technological solution to demand volatility and operational inefficiency, our analysis demonstrates that their effectiveness crucially depends on ports' competitive interactions and port users' choice decisions under different congestion conditions.

By developing a game-theoretical model with correlated demand randomness and imperfect information, we show that smart port development fundamentally alters the competition dynamics between ports. In addition to service price competition, ports compete through congestion information visibility, as congestion information disclosed to port users reshapes service choice behavior.

From the perspective of demand volatility, our analysis yields two key managerial insights. First, the value of developing smart ports is not monotonically positive. When demand shocks across competing ports are moderately correlated and information accuracy improvement is insufficient, developing smart ports can paradoxically amplify demand volatility rather than mitigate it (Proposition 1(iii)). This implies that port operators should assess the correlation structure of their demand environment before committing to smart port investments. Ports that serve highly overlapping shipping networks and face moderately correlated demand shocks (e.g., in regional port clusters such as those in Northern Europe and Southeast Asia) face the greatest risk of falling into the smart trap. For such ports, the managerial prescription is not to avoid smart port development, but to ensure that smart port development achieves a sufficiently high accuracy improvement to ensure the positive effect of demand data visibility.

Second, the outcome regarding Prisoner's Dilemma (Corollary 2) reveals that when both ports independently choose not to develop smart ports, the outcome is collectively worse (i.e., higher congestion disutility for port users, lower port profits, and elevated emissions) despite joint smart port developments being Pareto optimal. This coordination failure implies that unilateral decision-making is insufficient; port authorities or regional governance bodies should consider joint technology adoption programs, coordinated investment subsidies, or information-sharing agreements that help competing ports internalize the systemic benefits of joint smart port developments.

From the perspective of service capacity, our analysis reveals that capacity plays a pivotal role as a moderating variable that shifts the balance between two competitive dimensions. Specifically, Corollary 1 shows that as service capacity tightens, price competition weakens while congestion-driven competition intensifies, fundamentally altering the strategic environment in which smart port decisions are made. This has two practical implications for port operators. First, ports with tight capacity constraints should recognize that smart port development carries higher strategic risk, because the congestion-driven competition may intensify in certain conditions. Under such conditions, investing in capacity expansion before or alongside smart port development is essential as a strategic prerequisite that shifts the competitive balance back toward price competition, where smart port development is more likely to yield net benefits (Proposition 1(iv)). Second, our environmental analysis (Proposition 4) reinforces this core message. When capacity is insufficient and demand correlation is moderate, joint smart port developments may worsen environmental outcomes. For policymakers, this means that when assessing the environmental benefits of developing smart ports, they should link such subsidies to the port capacity, rather than treating technological investments and infrastructure expansion as mutually exclusive policy measures.

These findings contribute to the literature by showing that congestion information visibility plays a dual role: it enhances operational responsiveness while simultaneously reshaping port users' choice decisions and competitive dynamics. By explicitly modeling this tension, our work provides a more nuanced understanding of when and how smart port initiatives can improve congestion management and system resilience. While our study offers a systematic analysis of the smart trap phenomenon, it rests on several simplifications that open concrete avenues for future investigation. First, we assume that congestion information disclosed by a smart port is accurate and credible. In practice, cybersecurity threats such as data manipulation and spoofing could lead port users to discount disclosed information, which may reduce the benefit of smart port development and push the system toward a situation where the smart trap is more likely to arise. Second, our binary smart port development decision could be generalized to a continuous investment choice, where each port selects an information accuracy level at increasing marginal cost. This allows us to examine whether technological differentiation can serve as an equilibrium coordination device that resolves the Prisoner's Dilemma. We leave these as promising research directions that are beyond the scope of this paper.

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