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The impact of vessel speed reduction on port accidents

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ABSTRACT

Reduced-speed zones (RSZs) have been designated across the world to control emissions from ships and prevent mammal strikes. While some studies have examined the effectiveness of speed reduction on emissions and mammal preservation, few have analyzed the effects of reduced ship speed on vessel safety. Those few studies have not yet measured the relationship between vessel speed and accidents by using real accident data. To fill this gap in the literature, this study estimates the impact of vessel speed reduction on vessel damages, casualties and frequency of vessel accidents. Accidents in RSZ ports were compared to non-RSZ ports by using U.S. Coast Guard data to capture the speed reduction effects. The results show that speed reduction influenced accident frequency as a result of two factors, the fuel price and the RSZ designation. Every $10 increase in the fuel price led to a 10.3% decrease in the number of accidents, and the RSZ designation reduced vessel accidents by 47.9%. However, the results do not clarify the exact impact of speed reduction on accident casualty.

1. Introduction

Vessel speed reduction (VSR) programs have been implemented across the world to control the emission of pollutants. The rationale of the program is that reducing the vessel speed is expected to reduce fuel consumption, thereby decreasing emissions. For example, in 2001 the Port of Los Angeles designated reduced speed zones (RSZs) 20 nautical miles (nm) from the port to control ship emissions. Since then, more ports have participated in similar initiatives, including the Port of San Diego (POSD) and the Port of New York and New Jersey (PONY). On the other hand, VSR programs have been pursued in some areas to preserve endangered marine species. For instance, (Hazel et al., 2007) and (Vanderlaan and Taggart, 2007) provided empirical support that reduced vessel speed could reduce collision risks for mammals. (Hazel et al., 2007) demonstrated that turtles can flee twice the distance when the vessel speed decreases from 19 km/h to 4 km/h. An estimation by (Vanderlaan and Taggart, 2007) suggested that the probability of lethal injuries by ship collision for whales increased from 0.21 to 0.79 as vessel speed changes from 8.6 to 15 knots. Along this line, this paper is motivated by the hypothesis that if reduced vessel speed prevented accidents involving mammals, then it could also reduce vessel accidents. This is because, with lower vessel speed, navigators can enhance awareness and buy their time in responding to approaching ships, preventing precarious driving and reducing collision risks.

While some studies and our intuition tentatively suggest that vessel speed can affect accident rate, no studies formally tested whether there exists a significant relationship between the two. The most relevant studies on this issue can be divided into two groups. The first group consists of studies that adopted engineering approaches to investigate vessel speed and accidents. They developed simulation or programming models to describe the environment at a certain port and computes collision possibilities according to vessel speed. However, the studies investigated only a specific port at a time with many assumptions imposed in modeling. Moreover, they did not measure actual effects of vessel speed on accidents using the real accident data. The other group of the studies used econometric models to estimate casualty rates or damage costs of given vessel accidents. They mainly identified determinants that intensify accident damage, i.e. vessel and accident type. Nevertheless, they did not take vessel speed into consideration, and they only conducted ex-post analysis, i.e. they only considered accidents that already occurred. This way, it was difficult to examine accidents that have been kept from happening in certain environments.

To fill the gap in the literature, this paper examines the effects of vessel speed on damages, casualty and frequency of vessel accidents. Specifically, this paper investigates how the vessel speed affected 1) the accident damage and casualty level of given accidents and 2) accident frequency in a port level. For the latter, this study was the first to conduct that kind of analysis to the authors' knowledge. U.S. Coast Guard (USCG) data were collected for the analysis because the U.S. was one of the most active implementers of VSR, and the data set contained a large number of accident

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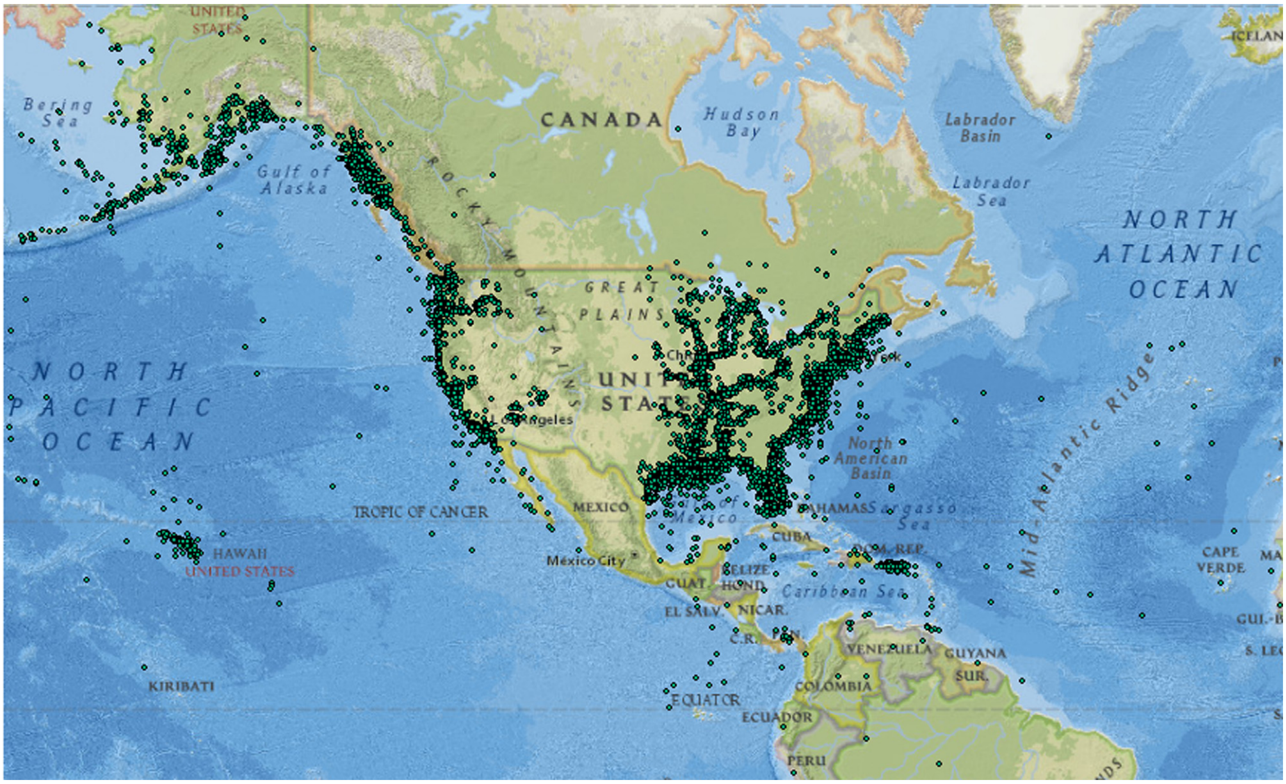

Fig. 1. A plot of U.S. accidents.

profiles. Estimating the effect of the vessel speed was challenging because speed was not recorded in each accident profile. However, this issue was addressed by comparing accidents in RSZ ports with those in non-RSZ ports. With all other factors being equal, differences in accidents between RSZ and non-RSZ ports were found to be attributable to differences in the vessel speed. Fig. 1 shows locations of vessel accidents in USCG data. Vessel accidents occurred mainly in coastal waters and inland waterways, where the vessel collision risk is high. The analysis was confined to coastal ports since it allowed us to observe clear distinction of vessel accidents between RSZ and non-RSZ ports. The analysis necessitated to separate RSZ accidents from non-RSZ ones and to generate accident frequency data at the port level from USCG data. Although the ArcGIS program was used to collect detailed data at this level, this task required substantial work. The detailed procedure for extracting necessary information from USCG data is described later.

To estimate the effects, three econometric models were used to handle different characteristics of damage, casualties and frequency data. First, damage was estimated using the tobit regression model. This was because the accident data showed many cases of zero damages, which called for censored distribution for damage data. Second, the zero-inflated regression model (ZINB) was employed to measure casualty counts. Previously, most of count data has been analyzed by using ordinary negative binomial model (NB) when the count data had unequal mean and variance structure. This was necessary especially for accident data because the number of casualties varied widely across geographic locations and environmental conditions, making the variance much greater than the mean. Although NB had some merits, it implicitly assumed that all ship accidents could necessarily hurt human beings aboard ships. This could be problematic as all accidents would not involve human casualties aboard ships, i.e. some ship collisions or groundings would not inherently incur injuries or death. While these accidents could add to excessive zero counts in the data, they were not governed by negative binomial distribution in a stricter sense, so the estimates of NB could be biased. Addressing this problem was possible through ZINB, which assumed two separate probability distribution for zero accidents. One process predicts accidents that necessarily produce zero casualty (accidents that are "safe for human" by their nature), and the other incorporates accidents, which happen to be zero casualties in spite of their inherent high risk (accidents that are hazardous to human but casualties do not occur by chance). A specification test was used to show that ZINB was more proper than NB for our casualty data. Lastly, we measured accident frequency through the panel NB regression model. The records of frequency were panel data covering accidents at coastal ports from 1992 to 2011. In this case, the latent effects that are specific to an individual port had to be controlled to correctly specify the estimation model (Chin and Quddus, 2003).

The rest of this paper is organized as follows: Section 2 reviews previous studies on vessel safety which adopted engineering or econometric approach. Section 3 develops damage/casualty and frequency estimation models. Section 4 details the data collection procedure and source of data. Section 5 analyzes the results, and Section 6 concludes with suggestions for future research.

2. Literature review

Vessel speed has been considered as a crucial factor to analyze ship accidents in engineering literature. Brown (2002) developed a simplified collision model to identify how ship speed, collision angle, ship type, and ship displacement affect damages in ship collisions. Generating random collision scenario, the study found that ship speed could have significant effects on ship damages. Mou et al. (2010) estimated the effects of ship speed, size and course to the closed point of approach (CPA), which was a widely used indicator describing collision risks. They found that CPA decreased in vessel speed while it increased in ship speed variation. Some studies proposed mathematical models to analyze ship collision incorporating ship speed even though they did not explicitly present the tractable relationship between speed and collision. Szlapczynski (2006) proposed a ship collision risk measure that considered ship location, speed and cruising course. A strength of his model was its flexibility to be integrated with existing ship domain (range of ship movements) models. Goerlandt and Kujala (2011) developed a probabilistic model to predict probabilities, frequency, location, and consequence of ship collisions. They validated their model by applying it to shipping routes around the Gulf of Finland. Qu et al. (2011) suggested three indices to measure ship collision potential based on speed, speed variation and the number of overlapping ship domain. To justify their indices, they argued that higher speed and speed variation could raise possibility of ship collision. Those studies described mechanisms that ships collided with each other in detail using rigorous numerical simulations.

Estimating the number of casualties and vessel damage is another area that has been frequently examined. Talley (1996) initiated a stream of research by analyzing casualty of container ship accidents. While previous studies focused on frequency of accidents, his analysis had a closer look at the magnitude of each accident, i.e. the number of the injured, the dead and damage costs. Later, Talley (1999) and Talley et al. (2006) conducted similar analyses using different vessel types and subjects. Yip (2008) also analyzed casualties in accidents, but unlike studies conducted by Talley, he included all ship types in a single estimation model. The results in the paper suggested that vessel and accident types were the main determinants for the number of casualties. Weng and Yang (2015) investigated fatalities in vessel accidents and developed two types of accident models complementary to each other: 1) a binary logistic model to predict the probability of fatal accidents and 2) a zero-truncated negative binomial model to estimate the number of fatalities. Yip et al. (2015) examined ferry and cruise ship accidents. After estimating crew injury determinants, they further investigated the effects of crew injuries on passenger ones. In this way, they found that there existed a positive relationship between them, suggesting that the crew played a crucial role in keeping passenger safety. Jin (2014) studied factors affecting vessel damage and crew injuries of fishing vessels. The paper showed that accident type, ship characteristics and weather conditions as well as distance from accident location to shore were significant determinants.

Reviewing past studies, gaps were present in literature. As for studies of ship accidents in engineering literature, they did not address the actual effects of vessel speed on accidents. Moreover, their scope of analysis was mostly confined to a single port or interactions of two ships. On the other hand, studies that estimated damages and severities by ship accidents did not incorporate ship speed or related variables into their estimation models. Moreover, they examined only the accidents that already happened but not the ones that might have been prevented from occurring.

3. Estimation model

3.1. Accident damage and casualty estimation model

A number of studies proposed unique estimation models of accident damages and casualty. Damage and casualty estimation models developed in this paper largely follow the line of previous models. Nevertheless, since our focus is mainly on the speed reduction effects, only factors that are most relevant to vessel speed are considered. The models can be expressed as a following functional form,

$$D_i = f\left(\mathrm{t_i}, \mathrm{a_i}, \mathrm{v_i}, \mathrm{d_i}, \mathrm{s_i}\right), \tag{1}$$

$$C_i = g\left(\mathrm{t}_\mathbf{i}, \mathrm{a_i}, \mathbf{v_i}, \mathbf{d_i}, \mathbf{s_i}\right). \tag{2}$$

^{D}i and ^{C}i indicate the damage cost and the number of casualties,[1] respectively where subscript i denotes an accident profile. $^{f}(\cdot)$ denotes the function that determines damage costs, and $^{g}(\cdot)$ casualty numbers. $\mathrm{t_i}$ is a vector of time variables when an accident happened, i.g. year and seasons. One can expect that accidents would occur less frequently with time passage since more strict safety measures develop over time. In addition, accidents can happen more frequently in a specific season due to different temperature and precipitation. $^{\mathrm{a}}{}_{\mathrm{i}}$ represents a vector of accident types, i.g. collision, allision, capsizing, evasive maneuvering, and grounding. A collision happens when two ships collide with each other. An allision involves a ship striking a stationary object other than ships. Capsizing is referred to accidents that ships are turned over. Evasive maneuvering is an accident from abrupt movement of ships to avoid a collision. Grounding happens when ships run right on seabed. It is expected that capsizing and collision would result in more damage and casualties over other accident types. Although there are many other accident types such as explosion and equipment failure, we excluded them because those accidents would not be affected by vessel speed.

$\mathrm{v_i}$ denotes a vector of vessel characteristics, i.e. ship types, ship sizes and nationality of ships. As for ship types, considering only cargo ships, tankers and passenger ships was reasonable because those ships are main regulatory targets of speed reduction. Which vessel type would incur more damage is indeterminate, but we can suppose that passenger ships can be more susceptible to casualties than other vessels. Ship sizes can be represented by gross ton. The relationship between ship size and damage/casualty is indeterminate since, as Talley et al. (2006) noted, ships of greater size are less likely to be affected by weather but have bigger impacts due to their sizes. Nationality of vessels reflects regulation imposed by a country. Among ships calling at U.S. ports, U.S. flag vessels have to follow stricter safety rules in general, so it is assumed that U.S. flag vessels were less prone to vessel damages and casualties. $\mathrm{d_i}$ is the distance from the location of an accident to the nearest post of rescue team. Jin (2014) included a similar variable into his estimation model, "distance to shore". The rationale was that the more distant an accident from shore, the more intense the accident became since it required more time to take emergency measures. If this was the case, it seemed more reasonable to use "distance to rescue team" than to distance to shore to accurately reflect the difficulty associated with distance or time. $\mathrm{s_i}$ is a set of variables associated with vessel speed. Apparently, one would prefer the exact vessel speed at the moment of accidents to estimate the effects. As the figures were not available in most ports, we had to use a proxy variable for vessel speed-that is whether an accident happened at RSZ or other location. Intuitively vessels operating at higher speed can cause more damages and casualties.

The estimations for Eqs. (1) and (2) were conducted by tobit regression and ZINB. The former has been used in Talley et al. (2006) and Yip (2008) and the latter Shankar et al. (1997) and Weng et al. (forthcoming). The details of the estimation techniques are not covered in this paper, but readers can refer to the previous studies or Greene (2008).

3.2. Accident frequency estimation model

A characteristic feature of this paper is an accident frequency estimation at a port level. Since no studies developed the estimation model, we had to select the most relevant variables that could

[1] Casualties indicate the people harmed by vessel accidents, which can be obtained by summing the number of the injured and dead by accidents. Such a measure was used in Weng et al. (2016) Weng et al. (forthcoming).

Table 1
Descriptive statistics of variables.

Variable	Mean	S.D.	Min	Max	Description
Dependent variables					
DAMAGET	98	791	0	24918	Damage cost per vessel tonnage ($)
CASUALTY	0.044	1.211	0	80	Number of casualties (person) in an accident
Independent variables					
Month[a]					
M1	0.111	0.314	0	1	January
M2	0.102	0.303	0	1	February
M3	0.100	0.300	0	1	March
M4	0.082	0.275	0	1	April
M5	0.076	0.265	0	1	May
M6	0.075	0.264	0	1	June
M7	0.063	0.243	0	1	July
M8	0.059	0.236	0	1	August
M9	0.065	0.247	0	1	September
M10	0.078	0.268	0	1	October
M11	0.078	0.268	0	1	November
Accident type[a]					
COLLISION	0.131	0.338	0	1	Collision
ALLISION	0.329	0.470	0	1	Allision
CAPSIZE	0.010	0.100	0	1	Capsizing
EVASIVE	0.021	0.143	0	1	Evasive maneuvering
GROUNDING	0.509	0.500	0	1	Grounding
Vessel type[a]					
FRTSHIP	0.108	0.311	0	1	Freight ship
FRTBARGE	0.119	0.323	0	1	Freight barge
PSGM	0.024	0.153	0	1	Passenger ships with more than six people
TANKSHIP	0.063	0.243	0	1	Tank ship
TANKBARGE	0.205	0.404	0	1	Tank barge
TOWTUG	0.481	0.500	0	1	Towing vessel/tug boat
Other					
DISTANCE	15.1	44.2	0.251	1109	The distance between the point of the accident and the nearest USCG station (km)
USFLAG	0.847	0.360	0	1	U.S. flagships (indicator)
GROSST	5173.5	13104.4	0	187648	Gross ton of a vessel
Speed reduction[a]					
ACTIVE_ACCDT	0.045	0.208	0	1	Accidents occurring in active RSZs
INACTIVE_ACCDT	0.036	0.186	0	1	Accidents occurring in inactive RSZs
ALLRSZ_ACCDT	0.081	0.273	0	1	Accidents occurring in both active and inactive RSZs

[a] 1 if true and 0 otherwise.

explain accident counts at ports. The resulting estimation model is specified as follows:

$$F_{it} = h\left(\mathrm{n}_{it}, \mathrm{w}_{it}, \mathrm{r}_{it}, \mathrm{p}_{it}, \mathrm{s}_{it}\right). \tag{3}$$

F_i represents the expected accident frequency of accident, and subscript i and t denote a specific port and a year, respectively. $h(\cdot)$ is an estimated function of accident frequency. n_{it} is the number of vessels calling at a port. One can expect that as ship traffic increases, more accidents would occur. The problem was that the exact vessel number data was not publicly available. Hence, gross state product (GSP) of the state where port i is located was used as the surrogate for vessel numbers. The rationale of using the surrogate lies in that states with higher GSP, i.e. Port of L.A./Long Beach and Port of New York/New Jersey tend to induce more ship traffic. This way, Eq. (3) is replaced with,

$$\begin{aligned} F_{it} &= h\left(\mathrm{n}_{\mathbf{it}}\left(\mathrm{i}_{it}\right), \mathrm{w}_{it}, \mathrm{r}_{t}, \mathrm{s}_{it}, \mathrm{p}_{t}\right) \\ &= l\left(\mathrm{i}_{it}, \mathrm{w}_{it}, \mathrm{r}_{t}, \mathrm{s}_{it}, \mathrm{p}_{t}\right), \end{aligned} \tag{4}$$

where $l(\cdot)$ is an accident frequency function with vessel numbers expressed as total state income.

w_{it} indicates weather condition, i.e. annual precipitation and average temperature. Higher rates of precipitation are expected to worsen visibility and seaworthiness. Meanwhile, the priori sign of temperature on accident frequency is indeterminate. r_t means a vector of regulatory measures imposed on ships. For example, International Safety Management (ISM) code was enforced by the International Maritime Organization since 1998 to reduce human errors in ship accidents. Kokotos and Linardatos (2011) and Tzannatos and Kokotos (2009) found that the code prevented human-caused accidents, so the human-caused effect in the accidents was controlled. Thus, the priori sign of r_t is negative. s_{it} is a vector of speed variables, which is similar to the speed variables in Eqs. (1) and (2). As vessels have short response time to impending accident at higher speed the sign of s_{it} is positive.

p_t is the price vectors of marine fuel that vessels consume. The reason for incorporating p_t into the model is that the fuel price is closely related to optimal vessel speed. By cubic law, a moderate increase in ship speed would result in exponential hike of fuel consumption. Hence, shipping lines tend to lower operating speed of vessels when fuel price rises (Notteboom and Vernimmen, 2009). While s_{it} is only affected by RSZ designation, p_t affects all ships regardless of RSZ. Moreover, the effect of vessel speed by RSZ designation and of higher fuel price can be different. For instance, cargo ships should reduce their speed to 12 knots (15 knots for cruise ships) in RSZ, but ships facing higher fuel price outside of RSZ would reduce speed relatively less than the one at RSZ from their operating speed, i.g. from 25 to 20 knots. Therefore, we use both speed and price variables to reflect the different effects on the accidents. The model Eq. (4) was measured by the panel NB regression, which are described in Appendix A in detail.

4. Data collection and processing

Variables in the damage/casualty estimation are summarized in Table 1. Variable names and their description are presented in the first and last column, respectively. As dependent variables, damage cost per vessel tonnage (DAMAGET) and the number of casualties (CASUALTY) were used. To eliminate price effects, DAMAGET was

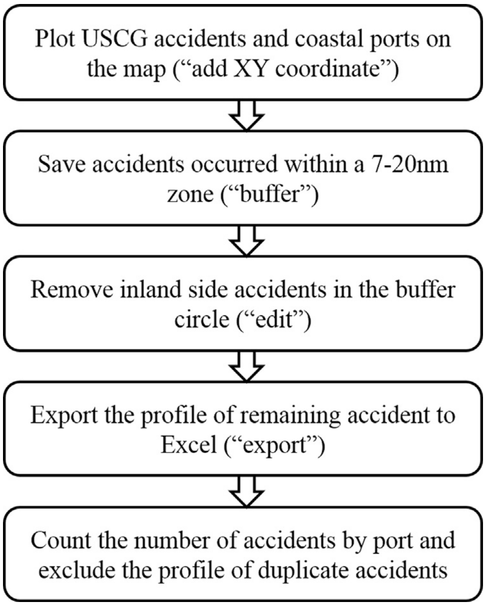

Fig. 2. The data-processing procedure using ArcGIS*.

converted into constant values by the Producer Price Index from the U.S. Bureau of Labor Statistics. Casualty counts were obtained by adding the number of the injured and dead in an accident. Summary statistics of CASUALTY suggested that the majority of accidents resulted in no casualties. It is was hypothesized that excessive zero accidents could have been caused by the two different processes. That is, there could have been zero accidents not only that inherently caused no harm to people, but also that could have seriously hurt people, however, the people were fortunate to avoid harm. If this was the case, the former and the latter should be treated distinctively. In the next section, it will be shown that zero accidents in our data were indeed caused by the two processes using a specification test.

In terms of months, accidents were evenly distributed in general, with winter season being slightly more frequent. For accident type, it was observed that grounding occurred most frequently, followed by allision and collision. Capsizing and evasive maneuvering rarely happened compared to other accident types. Among various ship types, about half of accidents involved towing vessels, followed by tank barge. Also, contributions of freight ships and barges to accident counts were not negligible while passenger ships and tank ships added little to the counts. The mean value of USFLAG indicated that majority of ships were registered in the U.S. DISTANCE represents the distance between the location of an accident and the nearest USCG station. The statistics suggested that most of the accidents happened not far from USCG stations. As for speed-related variables, ALLRSZ_ACCDT is an indicator variable that represents accidents that happened in all RSZ areas. ACTIVE and INACTIVE were obtained by splitting ALLRSZ into subtypes of RSZs, which are active RSZ and inactive RSZ.

Table 2 lists the subtypes of RSZs and their corresponding ports. Active RSZs were where the port authority regulated the vessel speed by initiatives. Regulated areas by VSR programs in the Port of Los Angeles/Long Beach (POLA) and the Port of New York/New Jersey (PONY) are typical examples of active RSZs. By contrast, inactive RSZs were where vessels naturally reduced their speeds because of strong current or narrow channel structures in port area. The Port of Oakland and the Port of Seattle fell into this category. In addition, these two types of RSZs differed in the range of vessel speeds. In active RSZs, general cargo ships were regulated to reduce their speed to 12 knots, and cruise ships, to 15 knots. On the other hand, ships generally operated at around 10 knots in inactive RSZs.

By analyzing two RSZ subtypes, we could differentiate speed reduction effects of two RSZs in detail. On the other hand, ALLRSZ_ACCDT mixes up the impact of both RSZ types, allowing for measuring overall effect of RSZs on casualty of accidents.

Table 3 lists the variables used in the accident frequency estimation model. FREQUENCY represents the annual number of accidents within the 7–20 nm range of each port. Accidents within the 7 nm range were excluded because most ports designated precautionary zones within this range to prevent collision risks. Hence, including the 7 nm range could have made it difficult to capture speed effect between RSZ and non-RSZ ports. Inland-side accidents were removed for the same reason. In addition, the maximum boundary was set to 20 nm because most RSZ ports regulate speed from the distance. This way, the effects of speed reduction could be identified more clearly.

FPRICE is the average oil purchase price per year, which served as approximated values for marine oil. FPRICE data were retrieved from the U.S. Energy Information Administration and converted into constant values, treating year 2009 as the base year. GSP is the gross state product in the state with the port, and it was used as a proxy for the number of vessel calls because complete vessel call data were not available for the 1992–2001 period. GSP figures were collected from the U.S. Bureau of Economic Analysis in chained dollars.[2] TPCP and TEMP are the total annual precipitation and the annual average temperature, respectively. The information on precipitation and temperature was available from the National Oceanic and Atmospheric Administration database. ISM represents the period that ships were under control ISM code. ALLRSZ_PORT indicates the ports that implemented speed reduction program regardless of RSZ subtypes. Likewise, INACTIVE_PORT and ACTIVE_PORT refer to the ports under inactive RSZ and active RSZ, respectively.

The USCG database underwent a major transition from the Marine Safety Information System (MSIS) to Marine Information for Safety and Law Enforcement (MISLE) in 2001.[3] These two databases had profoundly different reporting forms, so numerous variables were not usable after the merger of these two databases due to preponderance of missing values. For instance, too many accident profiles did not record weather conditions, propulsion types and hull construction types of vessels. Accidents with complete information amounted only about a hundred cases, whereas about 4500 cases were preserved if we abandoned the variables with frequent

[2] Chained dollars reflects real dollar values obtained by eliminating price effect over time, taking year 2009 as the base year. While normal constant values are calculated from a fixed list of goods and services, chained values are measured by updating the list every two successive years. Since GSP consists of numerous products, it is standard practice to remove price effect of GSP by the chained dollar method.

[3] For detailed guidance on processing MSIS data, see Talley et al. (2006).

Table 2
Subtypes of RSZs and corresponding ports.

Port	Start (year)	Range (nm)
Active RSZs		
Ports of Los Angeles & Long Beach	2001	20/40
Port of San Diego	2009	20
Port Authority of New York & New Jersey	2011	20
Inactive RSZs		
Port of Oakland	–	–
Port of Seattle	–	–
Port of Tacoma	–	–
Port of Houston Authority	–	–

Source: The Port of Los Angeles.

Table 3
Variables for measuring frequency.

Variable	Mean	Std. Dev.	Min	Max	Description
Dependent variables					
FREQUENCY	2.790	8.368	0	108	Annual number of accidents within the 7–20 nm range of each port
Independent variables					
FPRICE	27.501	14.856	10	58	Average oil purchase price in the U.S. ($)
GSP	477797	474193	34117	1993361	Gross state product in chained dollars ($)
TPCP	50.4	22.5	4	183	Total annual precipitation (mm)
TEMP	60.6	13.5	5	90	Annual average temperature (°F)
ISM	0.700	0.459	0	1	International Safety Management (indicator)
ACTIVE_PORT	0.017	0.128	0	1	Ports in active RSZs (indicator)
INACTIVE_PORT	0.089	0.285	0	1	Ports in inactive RSZs (indicator)
ALLRSZ_PORT	0.106	0.307	0	1	Ports in active and inactive RSZs (indicator)

missing values. It seemed more reasonable to work with 4500 cases because it would be more statistically consistent. Another reason was that key variables such as accident and ship types were still available as specified in Tables 2 and 3 while obtaining a rich data set spanning 1992–2011 year periods.

To obtain RSZ-related variables, it was necessary to separate accidents that occurred within RSZs. A major problem of using USCG data was that only the generic location of each accident was recorded (e.g., coasts, channels, and USCG administrative districts). Fortunately, latitudes and longitudes of each accident were reported, so ArcGIS was used to extract the accident profiles that suited our purpose. Fig. 2 summarizes the detailed procedure. First, coordinates of accidents (Fig. 1), USCG stations, and U.S. ports were plotted on a world map built in ArcGIS. Then a "buffer" function was used to set a 7–20 nm range for each port (see the empty circle in Fig. 3), and accidents that intersected with the range were retrieved. In this way, the number of accidents near coastal ports was calculated as FREQUENCY in Table 3. DISTANCE was obtained by a "near" function calculating the minimum distance between the USCG station and the location of the accident.

5. Results and discussion

5.1. Damage/casualty model estimates

Table 4 reports the estimates for damage and casualty models. The two rightmost columns show the incidence rate ratio (IRR), that is, a ratio change in λ_i based on a unit increase in explanatory variables. IRR was calculated by $\exp\left(\Delta x_{itk}\beta_k\right)$, where subscript k means the k-th variable. The estimates for independent variables other than speed variables are discussed first, followed by those for the latter. In lower side of the table, Vuong test statistic is reported, which was to determine whether ZINB should be favored over normal NB. The statistic was significant at 1% level, meaning that ZINB was more proper than NB. That is, accidents with zero casualty were truly generated by two distinctive underlying processes. Right below the statistic, alpha values (or dispersion parameters) are also recorded. They were also significant at 1% level, so we concluded that mean and variance were largely different. This suggested that ZINB was more appropriate than the zero-inflated Poisson model.

The positive sign of TREND was inconsistent with the estimates in Talley et al. (2006). This difference may be attributable to two factors: first, Talley et al. (2006) limited their analysis to passenger ships, whereas this study includes all ships types. Second, the results of this study included recent observations for the 2002–2011 year periods. In other words, damage costs would have naturally risen due to an increase in the property/cargo value over time. The coefficients of M2, and M10 were significantly higher than others, meaning that colder weather might have incurred more damage costs. For accident type, the greatest damage was found for CAPSIZE, followed by EVASIVE, COLLISION, ALLSION, and GROUNDING (base case) in decreasing order. Insignificance of USFLAG suggested that stricter safety standard on U.S. vessels hardly affected damage. For vessel types, FRTSHIP, PASSENGER and TANKBARGE were significant (TOWTUG as the base case), which was consistent with the findings of (Talley et al., 2006) and (Yip, 2008). GROSST or vessel size had no significant effects on damage. The coefficient of DISTANCE was insignificant, suggesting that there were no notable relationships between distance to USCG station and ship damage.

Moving onto the estimates of casualty model, TREND was insignificant, and only M10 and M11 were significant. For the type of accident, capsizing showed the largest number of casualties per accident, as in the case of damage. IRR of CAPSIZE ranged from 81.07 to 87.304, implying that capsizing accidents caused about 80–90 times more casualties than grounding (the base case) on average. For vessel type, only PASSENGER had the significantly higher impacts on casualties. IRR of PASSENGER shows that passenger ships caused 4.4–3.8 times more casualties than tug boats (the base case) in accidents. It was found that GROSST had notable effect on casualty counts, implying that people aboard bigger ships tended to be harmed more. DISTANCE was insignificant.

Now, speed reduction effects are explored in detail. Our initial hypothesis was that speed reduction would have reduced damage costs, but the results were opposite: ACTIVE and INACTIVE had *positive* effects on DAMAGET. The overall effect was described by ALLRSZ_ACCDT, which was also positive and significant. This pattern was the same for the casualty function, except that ACTIVE_ACCDT was insignificant. According to IRR results, inactive RSZs and all RSZs led to 6.1 and 4 times more casualties, respectively, than non-RSZ areas. If hastily concluded, the results suggested that vessels operating at lower speed caused more damage than those at higher speed. This was completely against our prior expectation, and the literature provided no theoretical or empirical evidence supporting these results. Nevertheless, it should be noted that the estimation models considered only those accidents that already occurred. This implied a possibility that less severe accidents may have been prevented from occurring in speed reduction zones, leaving only more severe accidents. To check this, we will describe what accident frequency results were produced in the next subsection.

5.2. Frequency model estimates

Table 5 shows the coefficients for the frequency estimation model. Hausman's specification test statistic was significant at 1% level, implying that fixed effect NB (FENB) was preferred to random effect NB (RENB: please see the details of FENB and RENB in Appendix A). Thus, only results for FENB are reported.

The positive sign of GSP implies that the larger the number of vessels or the higher the income level in neighboring areas, the higher the frequency of accidents. Note that GSP was used mainly for control purpose, and therefore no attempt was made to separate

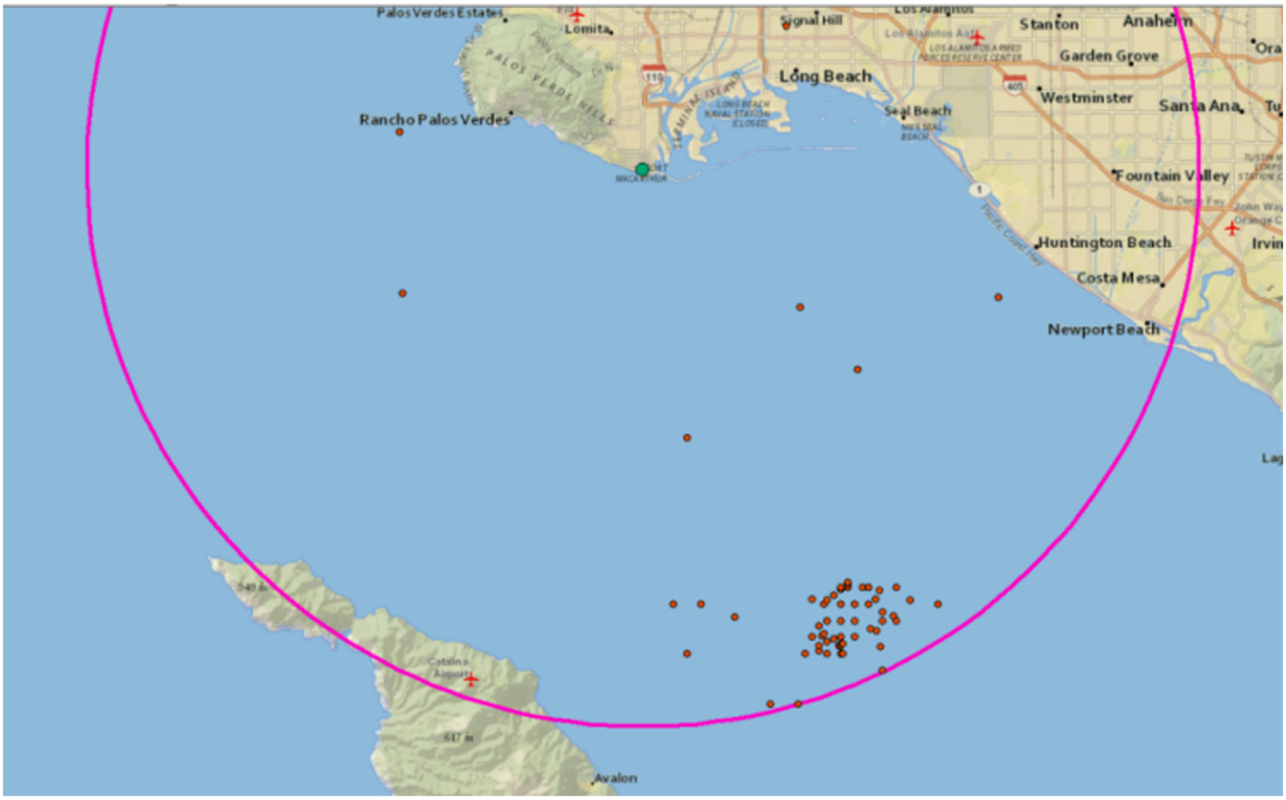

Fig. 3. A 20 nm zone at the Port of Los Angeles.

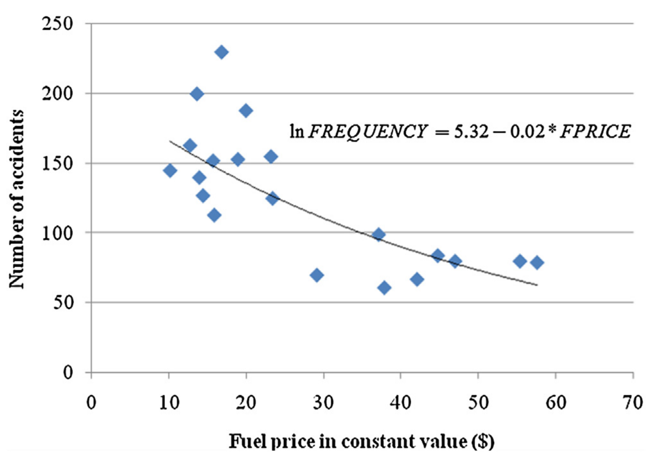

Fig. 4. A scatter plot of the fuel price and the number of accidents for 1992–2011.

the number of vessels from the income effect. TPCP, TEMP, and ISM were insignificant. Noteworthy is that FPRICE was negative and significant. It means that an increase in the fuel price motivated ship operators to reduce the vessel speed to reduce fuel costs, which in turn reduced the number of accidents. This reflects the "fuel price effect." As shown in Table 6, IRR of FPRICE was 0.989, which can be interpreted as every $10 increase in the fuel price reduced the number of accidents by 10.5% $\left(1 - 0.989^{10} \approx 0.105\right)$. The fuel price had a significant negative effect on the number of accidents. Fig. 4 provides a scatter plot of the fuel price and the number of accidents for the 1992–2011 period. The exponential line fits the relationship best between the fuel price and accident frequency ($R^2 = 0.616$).

ACTIVE_PORT, INACTIVE_PORT, and RSZ_PORT were negative. This clearly indicates that the frequency of accidents decreased due to speed regulation at the RSZ ports. Although the coefficient of ACTIVE was not significant ($p = 0.204$), it can be explained. First, RSZs were designated only recently, e.g. POLA in 2001, POSD in 2009 and PONY in 2011. Thus, the sample size of active RSZs was relatively small, which might not be sufficient to reveal a specific pattern. In addition, not all ships complied with VSR programs in the first year. For instance, about 56% of all vessels complied with VSR programs in 2001 at POLA, and the compliance rate increased to 90% only from 2007. By contrast, all vessels at inactive-RSZ ports had to reduce their speeds from the first place. This allowed us to observe the speed reduction effects more vividly. The estimated IRR for ACTIVE was 0.673, and that for INACTIVE was 0.4, implying 32.7% (1−0.673) and 60% (1−0.4) lower accident frequency than non-RSZ ports. The different magnitude of effects can be due to unequal speed limits of RSZ subtypes. Recall that vessels had to reduce their speed to 10 knots in inactive RSZs and to 12–15 knots in active RSZs. IRR of ALLRSZ implies that the overall effect of both RSZ subtypes contributed to a 47.9% (1−0.521) decrease in accident frequency.

To provide insights on the speed reduction effects, accident frequency at POLA is illustrated in Fig. 5. The reason for only considering POLA was that POLA started VSR program relatively early in 2001, so the pattern was more apparent than other ports such as POSD (started in 2009) and PONY (in 2011). Five-year moving average was calculated to smoothen the high variability of frequency among the years. The red line marks the starting year of VSR. The graph demonstrates that the average value has sharply decreased since the implementation of VSR.

In sum, two factors had notable influence on accident frequency: the fuel price effect and the RSZ policy. The fuel price effect was applicable to all coastal ports because of the universal nature of the price level. Vessels reduced their speed to save fuel when fuel prices were high. However, the RSZ program reduced the vessel speed to less than 12 knots for general cargo ships and 15 knots for

Table 4
Estimated results for damage and casualties+.

VARIABLE	Damage		Casualty (coefficient)		Casualty (incidence rate ratio)	
	ACTIVE/ INACTIVE	RSZ	ACTIVE/ INACTIVE	RSZ	ACTIVE/ INACTIVE	RSZ
TREND	**11814.3*****	**11789.2*****	0.007	0.005	1.007	1.005
	(3221.2)	**(3219.6)**	(0.033)	(0.032)		
M1	81181.2	80744.2	−0.169	−0.174	0.844	0.840
	(65439.6)	(65418.5)	(0.599)	(0.590)		
M2	**212481.2*****	**211796.2*****	0.110	−0.028	1.117	0.973
	(65119.4)	**(65058.9)**	(0.660)	(0.642)		
	85717.1	85495.1	−1.039	−1.006	0.354	0.366
M3	(65425.3)	(65422.6)	(0.667)	(0.655)		
M4	75838.9	75560.7	−0.986	−0.941	0.373	0.390
	(69024.6)	(69020.0)	(0.732)	(0.718)		
M5	−14201.2	−14481.2	−1.092	−1.103	0.335	0.332
	(71168.2)	(71163.4)	(0.729)	(0.722)		
M6	−70059.6	−70672.2	−0.192	−0.134	0.825	0.875
	(72985.3)	(72944.8)	(0.595)	(0.579)		
M7	1699.6	1715.9	−0.727	−0.689	0.483	0.502
	(75110)	(75115.9)	(0.823)	(0.810)		
M8	−12989.9	−13856.4	0.004	0.002	1.004	1.002
	(76488.3)	(76403.0)	(0.635)	(0.625)		
M9	91818.1	91209.5	−0.245	−0.223	0.782	0.800
	(73100.5)	(73061.2)	(0.680)	(0.664)		
M10	**210723.0*****	**211041.9*****	**1.058****	**1.114****	**2.881**	**3.046**
	(67795.9)	**(67786.9)**	**(0.535)**	**(0.523)**		
M11	74973.4	74639.5	**−2.504****	**−2.449****	**0.082**	**0.086**
	(70624.9)	(70614.4)	**(1.193)**	**(1.179)**		
COLLISION	**620535.4*****	**620508.9*****	**2.96*****	**2.888*****	**19.297**	**17.963**
	(44524.3)	**(44527.6)**	**(0.389)**	**(0.373)**		
ALLISION	**539932.9*****	**539602.0*****	**4.095*****	**3.922*****	**60.060**	**50.526**
	(35315.4)	**(35287.6)**	**(0.714)**	**(0.692)**		
CAPSIZE	**743952.7*****	**744178.1*****	**4.469*****	**4.395*****	**87.304**	**81.07**
	(124137.3)	**(124136)**	**(0.801)**	**(0.781)**		
EVASIVE	**717032.9*****	**718016.8*****	**2.81*****	**2.619*****	**16.609**	**13.716**
	(94300.5)	**(94211.9)**	**(0.662)**	**(0.631)**		
USFLAG	−16002.8	−16250.8	0.514	0.461	1.671	1.585
	(70466.3)	(70463.9)	(0.666)	(0.654)		
FRTSHIP	**360698.9*****	**360468*****	0.333	0.319	1.395	1.375
	(79624.9)	**(79625.4)**	(0.871)	(0.900)		
FRTBARGE	71793.6	71967.8	1.601	1.618	4.957	5.045
	(49305.0)	(49304.3)	(1.016)	(0.962)		
PASSENGER	**237443.0*****	**238402.8*****	**1.483****	**1.331****	**4.408**	**3.784**
	(86337.3)	**(86235.7)**	**(0.661)**	**(0.649)**		
TANKSHIP	**203535.4****	**203687.3****	1.269	1.208	3.558	3.348
	(89502.0)	**(89502.9)**	(0.800)	(0.786)		
TANKBARGE	−58623.9	−58631.7	−0.018	0.023	0.982	1.024
	(43479.5)	(43484.9)	(0.396)	(0.391)		
GROSST	−2.4	−2.4	**0.000***	**0.000*****	**1.000**	**1.000**
	(1.6)	(1.6)	**(0.000)**	**(0.000)**		
DISTANCE	156.0	157.4	0.003	0.003	1.003	1.003
	(279.1)	(279.1)	(0.004)	(0.004)		
ACTIVE_ACCDT	**198034.0*****		0.946		2.575	
	(64146.3)		(0.589)			
INACTIVE_ACCDT	**219483.7*****		**1.823*****		**6.193**	
	(73324.7)		**(0.587)**			
ALLRSZ_ACCDT		**207185.1*****		**1.392*****		**4.023**
		(50360.1)		**(0.438)**		
Constant	**−1.1e+06*****	**−1.1e+06*****	**−5.837*****	**−5.720*****	0.003	0.003
	(96664.2)	**(96596.9)**	**(0.914)**	**(0.889)**		
Vuong test statistic			**3.330*****	**3.250*****		
Alpha			**6.506*****	**6.260*****		
No. observations	4495	4495	4495	4495	4495	4495
Log-likelihood	−23448.942	−23448.969	−394.6846	−395.3546		

+standard deviations are in parentheses.
*, ** and *** indicate significance at the 10%, 5%, and 1% levels.

cruise ships, which were sharply lower than the navigating speed elsewhere.

It can be misleading to claim that speed reduction caused more damage and casualties as damage/casualty model proposed. Rather, it is more reasonable to think that relatively minor accidents might have been prevented from occurring in RSZs because speed reduction had a preventive effect on some accidents. If this was true indeed, analyzing only damages and casualty could have provided partial suggestions. Hence, it is important to use damage/casualty and frequency models complementarily to assess safety. This conflicts Talley's (1996, p. 245) view that "Since the casualty of an accident is conditioned upon the occurrence of an accident, the likelihood and the casualty of an accident are expected to have common determinants."

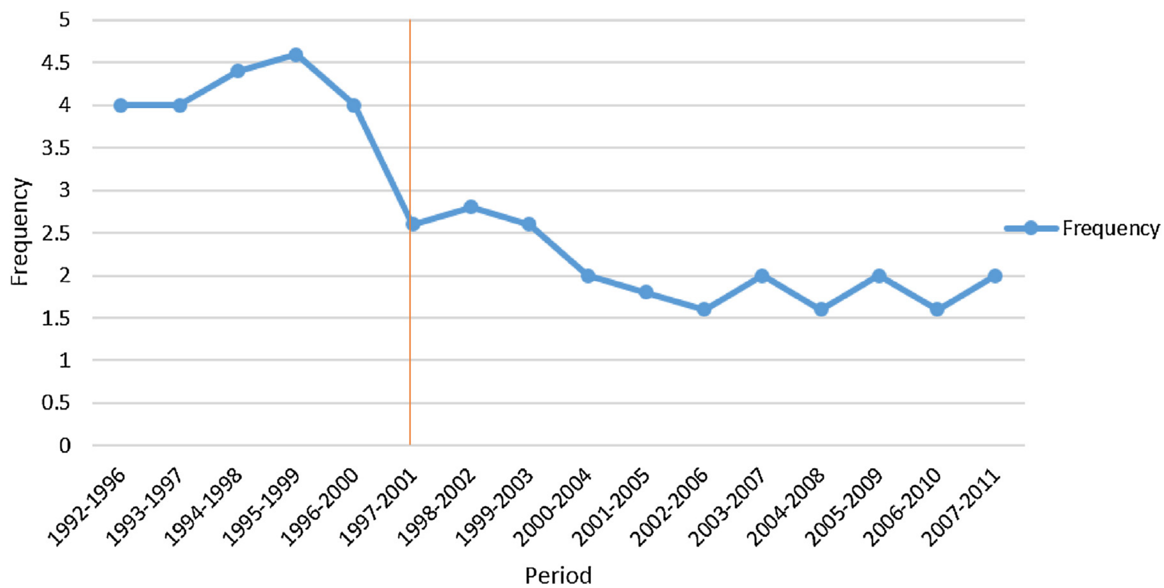

Fig. 5. Five-year moving average of accident frequency at POLA. (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)

6. Conclusion

This paper contributes to the literature in two ways. First, the paper is the first to develop damage/casualty and frequency estimation model of vessel accidents incorporating ship speed. Second, the paper estimated accident frequency at a port level, which previous studies have not explored yet. Both models were complementarily used to explore the safety issue regarding vessel speed since the damage/casualty model alone could not explain the accident deterrent effect of speed reduction. The effects of speed reduction of vessels were examined by comparing accidents at RSZ ports with those at non-RSZ ports. The challenging task of separating accidents in RSZs was made possible using ArcGIS. The analysis was limited to a 7–20 nm range of ports because this range was effective to reveal the speed reduction policy.

Table 5
The coefficient of frequency model.

	FREQUENCY	
VARIABLE	ACTIVE/INACTIVE	RSZ
GSP	**4.17e-07***	**4.38e-07***
	(2.38E-07)	**(2.36E-07)**
TPCP	−0.003	−0.003
	(0.004)	(0.004)
TEMP	0.003	−0.003
	(0.011)	(0.010)
ISM	0.002	0.013
	(0.102)	(0.102)
FPRICE	**−0.012*****	**−0.011*****
	(0.004)	**(0.004)**
ACTIVE_PORT	−0.397	
	(0.312)	
INACTIVE_PORT	**−0.918*****	
	(0.325)	
ALLRSZ_PORT		**0.653*****
		(0.243)
Constant	1.126	0.991
	(0.688)	(0.675)
No. observations	900	900
Hausman's test statistic	132.53***	56.3***
Log-likelihood	−1214.353	1215.043

Table 6
The incidence rate ratio of frequency model.

	FREQUENCY	
VARIABLE	ACTIVE/INACTIVE	RSZ
GSP	**1.000**	**1.000**
TPCP	0.998	0.998
TEMP	0.998	0.998
ISM	1.002	1.013
FPRICE	**0.989**	**0.990**
ACTIVE	0.673	–
INACTIVE	**0.400**	–
RSZ	–	**0.521**
Constant	3.081	2.694

At first, the results of the damage/casualty model showed that speed reduction intensified vessel damages and incurred more casualties per accident. To explain this unconvincing phenomena, accident frequency estimation was further conducted. In contrast to what damage/casualty model suggested, frequency estimation reported that speed reduction deterred vessel accident through two channels: the fuel price effect and the RSZ effect. Specifically, every $10 increase in the fuel price led to a 10.3% decrease in accident frequency. The effects of active RSZs on accident frequency was not apparent, which may be due to the small sample size and low compliance rates at the initial stage of implementing the policy. In inactive-RSZ ports, however, speed reduction effectively prevented accidents. Overall, RSZ programs reduced accidents by 48%. Combining two conflicting results, we concluded that potential accident with relatively small damages and casualty was avoided through speed reduction, leaving only impactful accidents in RSZ area. Nevertheless, whether speed reduction actually decreased damages or softened casualties was not clear.

This paper comes with some limitations. First, although the real speed data of vessels were more appropriate to be employed, the effects of speed reduction was assessed only by comparing RSZ ports with non-RSZ ones due to the lack of data. POLA recorded the vessel speed in RSZs to check whether vessels reduced speed in coordination with other authorities. In this regard, future research should use the data with accident profiles to validate the results of this paper. Second, the analysis considered gross state product instead of the number of vessels in the frequency analysis. The complete vessel data set may be used to validate the results. Third, numerous variables i.e. visibility, weather condition, were omitted due to preponderance of missing data. If available, a complete data set in other countries can be employed to draw robust conclusion. Fourth, when extracting accident profiles, we applied 7–20 nm range to all ports without considering hydrographic and geographic condition of each port to make the analysis in manageable fashion. This might have caused some biases that potentially affected the conclusion of this paper. Incorporating hydrographic and geographical characteristics would be another area of future research.

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Appendix A.

Accident frequency data in this paper were panel data from 45 coastal ports spanning the 1992–2011 period. Each port had its own characteristics that could contribute to accidents, such as geographic features and current strength. This port-specific effect was another source of variations in the analysis. If the port-specific effect is not sufficiently controlled for, the resulting estimates can be biased through the omission of variables. In the same manner, (Chin and Quddus, 2003) stated that t-ratios for estimated coefficients can be inflated unless the effect is considered. This effect can be incorporated by the panel NB regression model in (Hausman et al., 1984). Consider variable y_{it} that follows a NB distribution for a specific port *i* at time *t*. Then, NB with a port-specific effect can be represented as

$$y_{it} \sim NB\left(\gamma_i\lambda_{it,}\delta_i\right), \quad \text{where} \lambda_{it} = \exp\left(\mathrm{x'}_{\mathrm{it}}\beta\right) \; i = 1, 2, \ldots, N, \; t = 1, 2 \ldots, T \tag{A1}$$

λ_{it} denotes the mean rate of accidents for port i at t and δ_i is an overdispersion parameter

δ_i has the subscript *i*, meaning that the overdispersion rate is assumed to vary across ports. The time-invariant term γ_i represents the port-specific effect, which enters the model multiplicatively. The conditional mean and variance of y_{it} are expressed respectively as

$$\mathrm{E}\left(y_{it}|\mathrm{x_{it}}\right) = \gamma_i\lambda_{it}/\delta_i = \phi\lambda_{it,} \tag{A2}$$

$$\mathrm{Var}\left(y_{it}|\mathrm{x_{it}}\right) = \gamma_i\lambda_{it}\left(1+\gamma/\delta_i\right)/\delta_i = \phi\lambda_{it}\left(1+\phi\right). \tag{A3}$$

For convenience, the ratio γ_i/δ_i is usually substituted by ϕ_i. There are two types of panel NB models based on the treatment of γ_i. First, the fixed-effect NB model (FENB) estimates γ_i as separate indicator variables. Second, the random-effect NB model (RENB) treats γ_i as a randomly distributed variable not correlated with $\mathrm{x_{it}}$. FENB removes γ_i in the joint pdf by conditioning $\sum_{t=1}^{T} y_{it}$ such that the resulting joint pdf can be expressed as

$$p\left(y_{i1}, y_{i2}, \ldots, y_{it_i}|\sum_{t=1}^{T} y_{it}\right) = \frac{\Gamma\left(1+\sum_{t=1}^{T} y_{it}\right)\Gamma\left(\sum_{t=1}^{T}\lambda_i\right)}{\Gamma\left(\sum_{t=1}^{T} y_{it}+\sum_{t=1}^{T}\lambda_{it}\right)} \prod_{t=1}^{T}\frac{\Gamma\left(y_{it}+\lambda_{it}\right)}{\Gamma\left(1+y_{it}\right)\Gamma\left(\lambda_{it}\right)} \tag{A4}$$

On the other hand, RENB imposes the assumption that $\phi/\left(1+\phi_i\right)$ is beta-distributed with the parameter (*a*,*b*). In this case, the joint pdf is derived as

$$p\left(y_{i1}, y_{i2,}\ldots, y_{iT_i}\right) = \frac{\Gamma\left(a+b\right)\Gamma\left(a+\sum_{t=1}^{T}\lambda_i\right)\Gamma\left(b+\sum_{t=1}^{T} y_{it}\right)}{\Gamma\left(a\right)\Gamma\left(b\right)\Gamma\left(a+\sum_{t=1}^{T}\lambda_i+b+\sum_{T=1}^{T} y_{it}\right)} \tag{A5}$$

Unlike in (A4), additional parameters (*a*,*b*) are estimated for (A5). The MLE method is used to estimate β for each model such that the likelihood function in (A4) and (A5) are maximized.

The selection issue between FENB and RENB is discussed in (Cameron and Trivedi, 2005) and (Greene, 2008). FENB consumes more degrees of freedom as more parameters are to be estimated and assumes that the individual-specific effect can be correlated with explanatory variables. RENB is the opposite. Despite requiring fewer degrees of freedom, RENB makes a stronger assumption that the individual-specific effect is not correlated with explanatory variables. To determine the appropriate model between the two, Hausman's specification test (Hausman, 1978) can be used.

This test is based on the idea that RENB estimates are asymptotically inconsistent if the assumption of RENB (no correlation) does not hold. RENB estimates are consistent if explanatory variables and individual-specific effects are not correlated. On the other hand, FENB estimates satisfy consistency in any case when there is an increase in sample size. Hence, it follows that the difference between them should not be systematically large if both types of estimates are consistent. This means that the estimates of both FENB and RENBs approach a similar value, making the difference between them insignificant. In this case, it is desirable to use RENB because it requires fewer degrees of freedom while satisfying the underlying assumption of the model. To test this, the chi-square statistic proposed in (Hausman, 1978) is given by

$$x_{K-1}^2 \sim \left(\hat{\beta}_{\mathrm{FE}} - \hat{\beta}_{\mathrm{RE}}\right)' \mathrm{Var}\left(\hat{\beta}_{\mathrm{RE}}\right) - \left(\mathrm{Var}\left(\hat{\beta}_{\mathrm{RE}}\right)\right)^{-1}\left(\hat{\beta}_{\mathrm{FE}} - \hat{\beta}_{\mathrm{RE}}\right) \tag{A6}$$

where $\hat{\beta}$ is the vector of estimated coefficients and $\mathrm{Var}\left(\hat{\beta}\right)$ is the covariance matrix of estimated coefficients. The subscripts FE and RE denote estimates under fixed and random effects, respectively. The statistic follows a chi-square distribution with the degree of freedom *K-1*, and *K* means the number of coefficients. If the statistic is significantly high, then the null hypothesis that both $\hat{\beta}_{\mathrm{FE}}$ and $\hat{\beta}_{\mathrm{RE}}$ are consistent is rejected. In other words, there exists a systematic difference between $\hat{\beta}_{\mathrm{FE}}$ and $\hat{\beta}_{\mathrm{RE}}$. In that case, $\hat{\beta}_{\mathrm{FE}}$ is the better choice.

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