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Potential demand for coastal shipping in Queensland: a behavioural econometric analysis

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ABSTRACT

Road freight transport presently dominates in Queensland due to the current restrictive coastal freight transport regulations. This study presents a discrete choice experiment administered to a sample of shippers and freight forwarders to elicit their preferences for road, rail, and sea transport. The results reveal that about 30% of the choices of 64 company representatives were for the coastal shipping option. Model estimates suggest a willingness to pay about 20 AUD/hour for saving one hour of transit time in the corridor, a higher direct elasticity for road transport with respect to cost, a higher direct elasticity for sea transport with respect to time, and an effect of road user charge on shifting from road transport. The results also show the tendency of half of the sample to ignore either transport time or cost (if not both) in their mode choice decisions, and in this case, the willingness to pay increased to about 30 to 44 AUD/hour for decision-makers not ignoring time and cost in their decisions. Findings also suggest that freight decision-makers evaluate cost and delay attributes of modes in correspondence with risk factors.

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Freight transport; choice experiments; stated preferences; willingness to pay; short sea shipping

1. Introduction

The global growth of freight transport requires continuous improvements in the optimization of supply chains, including transport mode allocations. Knowledge about the preferences for alternative transport modes is essential for improved utilization of the available options that translate into increased efficiency and quality of freight transport systems. Coastal freight shipping can be such an option within freight transport systems. Coastal shipping can be advantages over competing modes due to offering of services at lower freight rates due to economies of scale and distance, the mitigation of possible freight damage due to the inherent nature of the movement, and the suitability for over-dimensional cargoes that cannot be loaded on trucks or trains (Paixão and Marlow 2002; Brooks and Frost 2004; Perakis and Denisis 2008). Moreover, coastal shipping does not entail public costs for building infrastructure, and port investment and maintenance costs are low when compared to public investments for the development and maintenance of road and rail infrastructure (Paixão and Marlow 2002). Important limitations of coastal freight shipping include the impossibility of door-to-door transport services, lack of collaboration between logistics providers, government policies, lack of incentives, and the requirement for intermodal arrangements

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(Raza, Svanberg, and Wiegmans 2020). Moreover, ports and/or terminal operators incur associated friction costs (e.g. waste, congestion) from the increased sea freight volume. Although coastal shipping is more energy efficient than other transport modes, it carries potential risks of harming marine assets (e.g. coral reefs, habitats, ecosystems) due to cargo losses, accidents, pollution, and noise.

Coastal shipping is considered a freight mode option in Australia given the large distance between the country's population centers that are located in coastal regions. Yet, the market share of this freight mode in Australia currently accounts only for about 17% of the total domestic freight movement and shows a decreasing trend (Australian Government 2015). Although not supported empirically (Bendall and Brooks 2011; Bendall and Brooks 2011), it is believed in the Australian context that coastal shipping can be a competitive freight transport mode in corridors exceeding 2,200 km, while road transport is seen to dominate the market for distances below 1,500 km, and rail transport is mostly considered for distances between 1,500 and 2,200 km. Yet, mode choices by Australian freight shippers are seldom an all-or-nothing decision but rather involve risk considerations through route and mode allocation (Brooks et al. 2012).

The limited coastal shipping market share in Queensland (and Australia) is also attributed to the existing coastal trade regulation (Navigation Act 1912) that limits access to national ship operators or national flag vessels with the national crew. This regulation, named cabotage, is a form of protection for Australian-registered ships since it controls the right to operate sea transport within a certain territory by imposing Australian wages (among other restrictions). Cabotage increases freight transport costs and, given the level of competition in the freight and logistics industry, places national ship operators at a disadvantage when compared to foreign-flagged and foreign-crewed competitors.

With an estimated 83% of non-bulk freight volume on the Brisbane-Townsville corridor in Queensland currently being transported via road (Queensland Government 2019), this study aimed to analyze the potential demand for coastal shipping in Queensland as an alternative mode that could provide relief to a region affected by high infrastructure maintenance costs, growing road safety issues, and increasing road congestion. An increase in the demand for coastal shipping could make this mode a palatable option for the Queensland freight and logistics industry and hence could justify a review of the current coastal trade regulations. Notably, previous analysis of three national freight corridors (Perth-Melbourne, Melbourne-Brisbane, and Brisbane-Townsville) suggested that coastal shipping could be considered in light of reduced transit time and increased reliability that mitigates the risk of delay (Brooks et al. 2012). However, as suggested by Bolis and Maggi (2003), we argue that the freight transport mode choices should be studied in integration with the network and its logistics context, or so-called services, rather than in terms of transport mode in its general context.

Investigating the potential demand for coastal non-bulk freight shipping within the Brisbane-Townsville corridor addresses past and current discussions within the Queensland freight and logistics industry (Queensland Government 2019). While it is not expected that the entire freight volume would shift from existing modes to the sea one, this option could potentially take the pressure off the road network in the future.

Given the coastal shipping option is not currently available, a stated preference (SP) experiment with shippers and freight forwarders operating in Queensland was undertaken to assess their preferences for existing land transport modes (i.e. road, rail) and a hypothetical sea transport option (i.e. coastal).

This study contributes to the literature by not only understanding whether demand for short sea transport exists in Queensland (and hence an appetite for modifying sea regulations exists as well) but also attempting to unravel the decisions makers' viewpoints on risk aspects combined with their mode choice decisions by using a hybrid choice model. Moreover, this study contributes to the literature by considering numerous behavioral aspects such as the possible effect of inertia in the decisions, the conceivable asymmetry in parameters when associated with an increase or decrease from a reference alternative and the possible non-attendance of attributes by some decision-makers.

The remainder of the manuscripts is organized as follows. Section 2 presents the literature review. Section 3 outlines the design of the experiment. Section 5 discusses the results and Section 6 provides the policy implications. Finally, Section 7 draws conclusions from this study and provides the study's limitations and ideas for future studies.

2. Literature review

A systematic literature review on the modal shift from road to short-sea shipping was undertaken by Raza, Svanberg, and Wiegmans (2020). As suggested by this review, the majority of research papers on coastal and short-sea shipping applied a descriptive approach and only a handful of papers offered empirical evidence on the factors affecting the choice of coastal shipping. Among those empirical studies, the majority of studies explored the coastal or short-sea shipping option in European countries.

A number of studies applied a qualitative analysis approach to obtain quantitative data on the potentials of coastal shipping and the significant factors that freight companies and shipping lines take into account when deciding about freight transport mode. The methods include Delphi method (Saldanha and Gray 2002; Venkatesh et al. 2017), fuzzy-AHP method (Jung, Kim, and Shin 2019), and qualitative inductive research (da Silva et al. 2022).

Chandra, Christiansen, and Fagerholt (2020) developed an optimization model to determine optimal route alternatives, ship types, shipment volumes and other shipping variables. This study, however, did not provide behavioural insights into the influential factors for the transport modal shift. Sambracos and Maniati (2012) studied the economic competitiveness of short-sea shipping and road transport in Greek by comparing the costs of these two modes. Konstantinus and Woxenius (2022) undertook a case study approach for the coastal shipping competitiveness in sub-Saharan Africa.

Looking at the literature, three studies have used stated preference choice experiments. Vega, Feo-Valero, and Espino-Espino (2021) undertook a stated preference survey to examine the route choice of short sea shipping in the EU in a post-Brexit scenario. This study did not compare short sea shipping with other transport modes such as rail or road. Kim, Kusumastuti, and Nicholson (2018) conducted a stated preference survey among shippers in New Zealand to investigate the factors affecting their transport mode choice across. It should be noted, however, that coastal shipping is currently available in New Zealand and this study aimed at investigating different policies to increase the market share, which is different from the Australian context. Using a discrete choice experiment, Brooks et al. (2012) examined the Australian domestic freight transport market by focusing on mode choice decision-making between land-based transport and coastal shipping. Findings from these studies included the presence of a significant trade-off by shippers regarding costs and perceived benefits of reducing transit time, enhancing on-time arrival reliability, and mitigating the risk of arrival delay (Brooks et al. 2012; Kim, Kusumastuti, and Nicholson 2018). Furthermore, a general preference of respondents for the established road and rail modes was found, but the authors also identified a value in obtaining increases in reliability for sea freight services (Brooks et al. 2012; Kim, Kusumastuti, and Nicholson 2018). Unfortunately, the results of the study by Brooks et al. (2012) are aggregated over three Australian freight corridors (Perth-Melbourne, Melbourne-Brisbane, and Brisbane-Townsville) and are not corridor-specific (Brooks et al. 2012). Hence, that study does not provide sufficient information about the potential demand for sea shipping on the Brisbane-Townsville (Queensland) corridor, which is the focus of the present study.

While the elicitation of individual preference structures is a common approach in the context of logistics choices, it is important to consider other factors such as environmental sustainability aspects, or risk minimization that could affect freight mode decisions. It is well established in the literature, that the perception of business risks (e.g. damage to reputation or change in logistics operations) or attitudes towards the environmental impacts of operation can affect business decisions such as mode choice (Kumar Dadsena, Sarmah, and Naikan 2019; Jung, Kim, and Shin 2019). Also, as argued by Bolis and Maggi (2003), the freight transport mode choices should be studied within its logistics network services and transport mode preferences could vary across regions and countries.

Given coastal shipping is not currently available in Australia, a revealed preference survey cannot be undertaken. Moreover, important indicators such as willingness to pay cannot be calculated through qualitative interviews or surveys. The optimization methods are useful tools for designing optimal transport network and service attributes but cannot reveal the behaviors and attitudes towards a new alternative. Therefore, stated preference choice experiments can overcome these challenges. Therefore, this study attempts to elicit the shippers and freight forwarders' preferences, and their willingness to pay for the hypothetical coastal shipping option within a specific corridor. Several advanced discrete choice models are applied to unravel the underlying behaviors, attitudes, and risk perceptions that could impact the transport mode choice. Section 3 discusses the discrete choice experiments and models.

3. Experimental design

3.1. Context

Queensland is the second-largest and third most populated state in Australia. The state's population is predominantly located along its coast that stretches over a length of about 2,300 km, with about half of the inhabitants being located in South-East Queensland, around Brisbane. However, important regional cities in the north of Queensland disperse the population and hence make freight transport challenging.

This study focuses on the freight corridor between Brisbane and Townsville, which covers a distance of about 1,300 km and is shown in Figure 1 Approximately 83% of the non-bulk freight volume in this corridor is transported via road, 10% via rail and the remaining 7% via international coastal shipping (Queensland Government 2019). Although road transport is considered the most flexible freight mode in Queensland (Mitchell and McAuley 2009), it is presently the most expensive option. The geographically dispersed nature of most freight tasks precludes rail from exploiting scale-induced cost advantage. Hence, long-distance non-bulk freight has largely shifted from rail to road. Rail is often used to transport long-distance bulk shipments, wherever there is an existing rail infrastructure in close proximity to shipper's locations (Mitchell and McAuley 2009).

Moreover, high development and maintenance costs of road infrastructure, significant road safety issues, and increasing road congestion (particularly in metropolitan areas of south-east Queensland) are reasons for exploring alternative freight mode options. While rail transport offers freight transport services at lower rates, it is facing issues such as the need for investments in upgrades of the railway system and maintenance of tunnels and bridges. Mitchell and McAuley (2009) argued that the mode choice in the Australian long-distance context depends on the nature of the freight and requirements of shippers as it affects the relative importance of cost of service and quality. For example, for perishable and high-value commodities, time-sensitive door-to-door services may matter to shippers rather than line-haul services. Currently, sea transport is selectively offered for non-bulk freight by ships under foreign flag.

4. Methods

A discrete choice experiment among shippers and freight forwarders was undertaken to elicit their preference for coastal shipping compared to existing road and rail transport modes. This method consisted of SP survey design and choice model estimations.

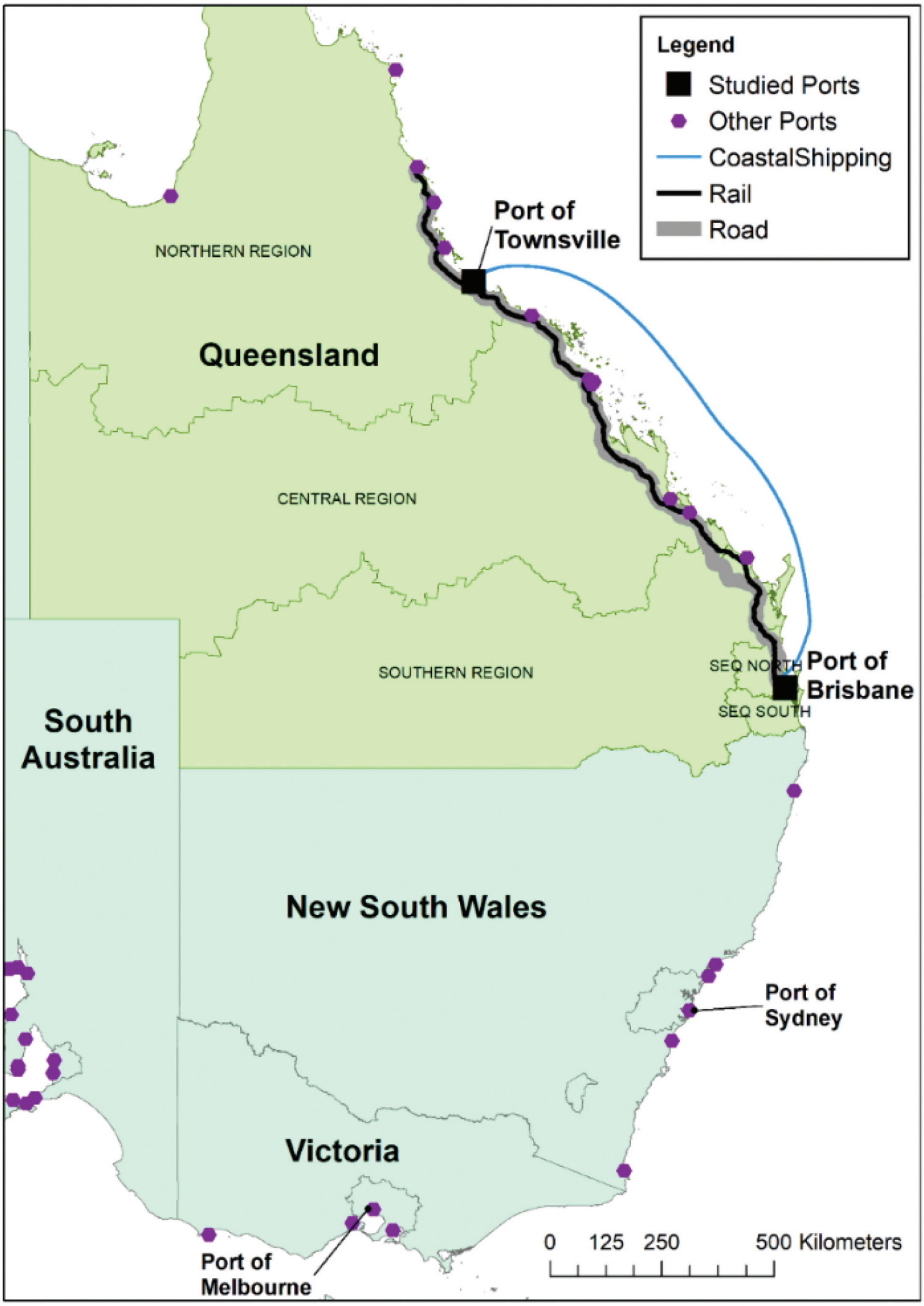

Figure 1. Brisbane-Townsville freight corridor.

Furthermore, a hybrid discrete choice model was specified by accounting for latent risk perception factors which may affect decision-making. Integrated choice and latent variable models, or so-called hybrid choice models, were first introduced by McFadden (1986), and further progress was made by Walker (2001). Hybrid choice models have been widely applied in the context of passenger travel behavior such as route choice, car ownership, departure time, and travel mode choice.

However, incorporating behavioral factors in the context of freight transportation is still limited to a few studies such as a qualitative study of behavioral biases of freight-forwarders towards intermodal transport (Elbert and Seikowsky 2017), and an investigation into mode choice of road transport operators (Bergantino et al. 2013).

Following the hybrid approach described by Walker (2001), the discrete choice model was enriched by incorporating risk perception latent variables in interaction with the observed variables of cost and delay. Latent risk factors were measured on the basis of respondents' rating, on a 1–5 Likert scale (1: no risk, . . . , 5: high risk), for 21 questions, and they were incorporated into the specifications of the choice model in conjunction with the analysis of non-observable heterogeneity through the estimation of latent class models. Accordingly, applying a hybrid framework incorporating the heterogeneity of taste and risk perception factors reinforces the added value of this study for the empirical literature in the context of freight transportation mode choices.

4.1. Data

An SP experiment was designed to collect preferences between road, rail, and sea transport. A questionnaire accompanied the SP experiment to collect information about respondent characteristics (e.g. age, gender, position in the company) and company characteristics (e.g. company size, freight-type movements, coastal shipping experience), risk perception factors as well as comments about their perception of the advantages and disadvantages of coastal shipping.

The target population included shipping and freight forwarding companies operating in Queensland. Given the absence of a public register for these companies, an online search allowed to identify shippers and freight forwarders with the potential for transporting freight on the Brisbane-Townsville corridor. Identified companies were contacted by phone to ensure that they indeed serviced this freight corridor, to verify their contact details and to notify them of the upcoming survey. Last, the survey was distributed in May 2017 to 348 shipping and freight forwarding companies with the assistance of the Port of Brisbane and the Port of Townsville given their collaboration with these customers.

4.1.1. Definition of the attributes

The identification of the relevant attributes for SP experimental design included a review of the literature on freight mode choice and revealed that cost and time were the most commonly considered attributes in discrete choice experiments. Moreover, service-related attributes such as frequency, flexibility, and reliability were identified as frequently used attributes to describe freight transport modes (Cullinane and Toy 2000; Reis 2014). Eventually, 14 attributes were identified which include tractability, service, environmental impact, frequency, distance, cost/price/rate, infrastructure availability, capability, inventory, loss/damage, commodity, transit time reliability, previous experience with coastal shipping, and speed.

A focus group with 13 representatives of the Queensland freight and logistics industry helped identify the most relevant attributes for the specific corridor from the compiled list. The participants were asked to rank the seven most important attributes (with the assumption that the remaining seven would be irrelevant), as well as to identify attributes that they might find relevant although not being considered in the literature. Furthermore, a discussion with the focus group participants revealed that there could be ambiguity in the definition of some attributes (e.g. the capability of transport modes could refer to the capability of trucks or vessels, but also the capability of administration). Eventually, four attributes were identified in the focus group discussion as most important and their average ranking by focus group participants confirmed their relevance. These include: cost (average ranging = 1.25), reliability (average ranking = 2.70), speed (average ranking = 4.10), and frequency (average ranking = 4.70). The remaining attributes had a low frequency of selection as relevant and/or a high average ranking, and hence the attributes considered for the SP experiment were (i) cost, (ii) service frequency, (iii) time, and (iv) delivery delay. Notably, the attributes were similar to the ones considered in the previous aggregate study about coastal shipping in three Australian corridors (Brooks et al. 2012).

4.1.2. Levels of the attributes

The focus group also assisted in determining the attribute levels. For example, the group discussion helped clarify that transit time reliability would be better understood as delivery delay, as an absolute measure would not be perceived and the concept of punctuality could be misinterpreted (Arencibia et al. 2015). Accordingly, the delivery delay was framed as the proportion of deliveries that is delayed on the Brisbane-Townsville corridor (Table 1). To determine the levels of the service frequency attribute, the advice from the focus group was used which broadly reflects the levels which Brooks et al. (2012), Arencibia et al. (2015) and Konstantinus and Woxenius (2022) applied in their work.

Current costs for road and rail modes were derived directly from selected freight service providers. Representatives from the Port of Brisbane offered estimates for sea freight costs. The focus group assisted in verifying cost level ranges shown in Table 1. The attribute levels for mode service costs considered the movement of a twenty-foot equivalent unit (TEU) container with a door-to-door service on the Brisbane-Townsville corridor, including costs associated with container return.

Costs were assumed within two scenarios: (i) the current road transport network; (ii) a future road transport network with a road usage charge. As the purpose of this study was to look at the potential shift from land, and in particular, road transport to coastal shipping, the second scenario was introduced as a possible policy measure to make the shift more likely. The road usage charge was assumed to be 600 AUD for one trip, an increase of the road transport costs by approximately 10–14% with respect to the current scenario. It should be noted that the estimate was derived from the review of current tolls for heavy diesel vehicles per kilometer (km) used in the European Union and New Zealand.

Table 1. Attribute description and levels.

Attribute	Description	Levels
Costs	Costs or freight rate for shipment of non-bulk cargo (a 20-foot shipping container or truckload equivalent of 30 m^3) for delivery on Brisbane—Townsville freight corridor.	Base scenario Road (AUD): 4,400; 4,900; 5,600 Rail (AUD): 2,200; 2,600; 3,000 Sea (AUD): 1,700; 2,600, 3,300 Toll scenario Road (AUD): 5,000; 5,500; 6,200 Rail (AUD): 2,200; 2,600; 3,000 Sea (AUD): 1,700; 2,600, 3,300
Service frequency	The number of services per week available by each mode for the Brisbane—Townsville freight corridor.	Road (services/week): 7, 10, 15 Rail (services/week): 4, 7, 10 Sea (services/week): 1, 2, 3
Transit time	The total amount of time (hours) for a door-to-door delivery on the Brisbane-Townsville corridor.	Road (hours): 19; 30; 36 Rail (hours): 36; 48; 72 Sea (hours): 48; 60; 72
Delivery delay	The proportion of all deliveries that is delayed on the Brisbane—Townsville corridor.	Road (%): 1; 4; 7 Rail (%): 3; 7; 10 Sea (%): 2; 6; 8

While reasons for different cost structures of the three freight modes were not investigated in more detail, the higher flexibility and shorter transit time of the road mode compared to rail and sea likely contribute to higher road mode prices (Mitchell and McAuley 2009). Table 1 presents the description and the levels of the attributes used in the SP experiment. It should be noted that the derived attribute levels for all three modes are similar to the ones used by Brooks et al. (2012). The attribute levels also comply with average road and rail freight cost estimates by haulage distance provided by Mitchell and McAuley (2009).

4.1.3. SP design

Given the attributes and their levels, the third task in the SP experiment design was the selection of the design type between full fractional, orthogonal, and efficient. The selection of the efficient design was motivated by the desire to obtain reliable estimates with a small sample size and the availability of prior information about parameters from previous freight mode choice studies. The respondents were asked to consider their company's perspective when choosing the transport mode options.

Specifically, focus group participants commented on parameters retrieved from existing studies and helped select the ones for the efficient design. The Ngene software (ChoiceMetrics 2018) was used to derive the design that minimizes the D-error, defined in terms of the asymptotic variance-covariance matrix. A pilot test with representatives from shipping and freight forwarding companies allowed to refine the parameters for the efficient design, and eventually the final design consisted of three blocks for each scenario (i.e. base, toll) that were randomly allocated to each respondent. Figure 2 presents an example of one of the 16 choice tasks that each respondent was asked to choose from (8 from one block of the base scenario, and 8 from one block of the toll scenario).

4.1.4. Decision-makers' characteristics

Along with respondent and company characteristics, the survey included questions about the perception of risks. Perceived risks (e.g. damage to reputation, the environmental impact of operations, change in logistics operations, see selected list in Figure 3) can affect business decisions such as mode choice (Kumar Dadsena, Sarmah, and Naikan 2019; Jung, Kim, and

Assume, you have recurring shipments of non-bulk freight (a 20-foot shipping container or truckload equivalent of 30 m^3) for delivery on the Brisbane-Townsville corridor. All freight rates reflect costs for a full-round trip (including container return to its origin).
Please consider the following situations from your company's perspective (including the experience with current mode(s) used, typical shipment types, etc.).

Choice task 1

Which mode would you choose? *(Hover over attributes for a detailed description.)*

	Road	Rail	Sea
Transit time	19 hours	72 hours	60 hours
Freight rate	$5,600	$2,600	$1,700
Services per week	15	4	2
Delivery delay	7%	7%	2%

I would choose:

○ **Road** ○ **Rail** ○ **Sea**

Figure 2. Choice task example.

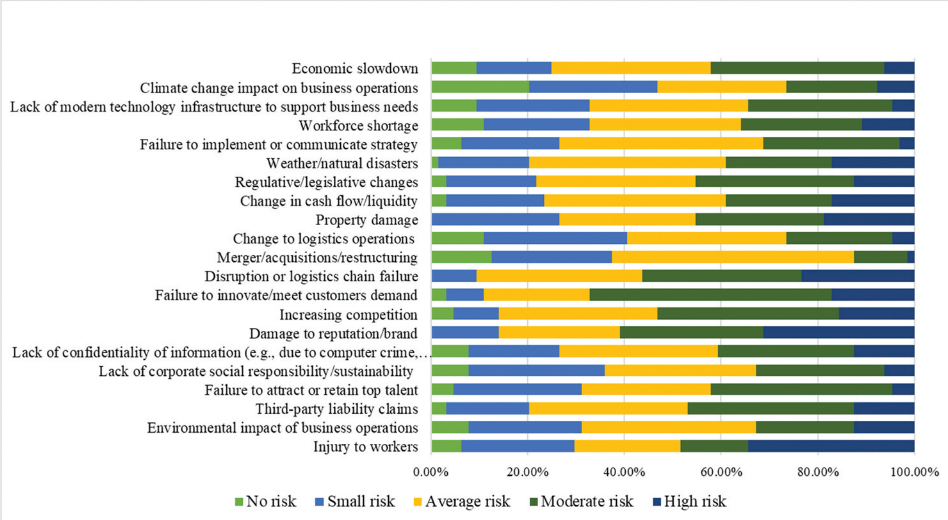

Figure 3. Percentage of respondents to risk factors.

Shin 2019). Accordingly, a list of statements was presented to the respondent to capture pre-determined risk factors which may not immediately determine mode choice but could indirectly influence mode decisions. Similar to the mode choice tasks, the respondents were asked to answer from their company's perceived business risks. It should be noted that the survey was distributed and collected by a survey company and the questionnaires were only forwarded to people who can make decisions at the company level or can transfer their company's perspective.

The latent variable indicators were expressed as Likert-type items of five points. The frequencies of the answers to the indicator questions are shown in Figure 3. A factor analysis was undertaken for different numbers of factors to re-identify the number of unobserved risk factors from the indicators based on their interdependencies. The chi-square statistics showed that four factors were adequate to explain the covariances among the indicators (P-value: 0.0365) as shown in Table 2. The reliability and adequacy of the sample were tested on the overall scale as well as for each item (considering Cronbach's alpha by dropping one item at each time). Cronbach's alpha test showed that all latent variable indicators shared covariance and most likely measure the same underlying concept (Cronbach's alpha >0.7 for all latent variables). Kaiser–Meyer–Olkin (KMO) test also indicated the correlation values and adequacy for the exploratory factor analysis (KMO of overall items: 0.85, KMO at the item level: between 0.72 and 0.93).

The first factor concerns the risk factors associated with the company's procedures and performances where the company is the principal player and is named *internal risk*. The second factor relates to the risks associated with a competitive market and is entitled *market risk*. The third factor indicates the perceived immediate operational risk and is named *immediate risk*. The fourth factor relates to questions about the external risk factors that are out of control of the company and is labelled *external risk*. This categorization is supported by the literature on operational risk management (Tupa, Simota, and Steiner 2017).

The correlation between these items and factors served as input in the measurement equations, which is jointly estimated with the mode choice model. Different specifications were tested where the latent variables relate to the dependent variable of mode choice either directly or in interaction with the observed variables. However, the fourth latent variable (*external risk*) was not statistically

Table 2. Reliability tests and exploratory factor analysis.

Factors	Item	Factor analysis 1	2	3	4	KMO	Cronbach alpha if an item is dropped	Cronbach alpha
Internal risk	I1: Injury to workers	0.438	0.521			0.92	0.86	0.88 (0.83–0.92)
	I2: Environmental impact of business operations		0.615			0.85	0.85	
	I3: Third-party liability claims	0.503	0.431			0.84	0.87	
	I4: Failure to attract or retain top talent	0.535	0.566			0.82	0.86	
	I5: Lack of corporate social responsibility/ sustainability		0.936			0.93	0.84	
	I6: Lack of confidentiality of information (e.g. due to computer crime, hacking, etc.)		0.588			0.81	0.86	
Market risk	I7: Damage to reputation/brand			0.634		0.80	0.70	0.75 (0.66–0.85)
	I8: Increasing competition			0.508		0.85	0.72	
	I9: Failure to innovate/meet customers' demand			0.650		0.72	0.67	
	I10: Disruption or logistics chain failure			0.470		0.79	0.72	
	I11: Merger/acquisitions/restructuring	0.562		0.401		0.85	0.75	
Immediate risk	I12: Change to logistics operations			0.571	0.800	0.87	0.44	0.62 (0.43–0.80)
	I13: Property damage	0.716			0.415	0.73	0.20	
External risk (*)	I14: Change in cash flow/liquidity	0.467		0.556		0.83	0.84	0.87 (0.82–0.92)
	I15: Regulative/legislative changes	0.409		0.710		0.88	0.85	
	I16: Weather/natural disasters	0.611				0.88	0.86	
	I17: Failure to implement or communicate strategy	0.488	0.416	0.424		0.90	0.85	
	I18: Workforce shortage	0.696				0.83	0.85	
	I19: Lack of modern technology infrastructure to support business needs	0.544				0.92	0.86	
	I20: Climate change impact on business operations	0.409	0.541			0.83	0.87	
	I21: Economic slowdown	0.470				0.86		

*Dropped latent variable from the analysis.

significant in the hybrid choice model and was eliminated from the model. The fact that the external risk factors are out of control, can explain this result.

4.2. Models

Mode choice models were estimated under the assumption that decision-makers were utility maximizers, and hence the utility of freight transport mode i for decision-maker n was expressed as the sum of a deterministic part V_{ni} and a stochastic part ε_{ni} *(Train 2009)*:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{1}$$

Given vectors of observable individual characteristics X_n and attributes Z_{ni} of freight transport mode i, a vector β of fixed parameters associated to X_n, and a vector β_n of random parameters associated to Z_{ni}, it was possible to rewrite the utility function of mixed Logit Model (MXL) as (Train 2009):

$$U_{ni} = \beta X_n + \beta_n Z_{ni} + \varepsilon_{ni} \tag{2}$$

Expressing the probability of choosing freight transport mode i as a logit model, and considering the density function $f(\beta_n)$ of the random parameters, resulted in the following probability (Train 2009):

$$P_{ni} = P(y_n|X_n, Z_{ni}; \beta, \beta_n, \Sigma_\varepsilon) = \int_{\beta_n} \frac{\exp(\beta X_n + \beta_n Z_{ni})}{\sum_j \exp(\beta X_n + \beta_n Z_{nj})} f(\beta_n)\, d\beta_n \tag{3}$$

where y_{ni} is the indicator of choosing mode i over alternative mode $j \neq i$. The elements of the vectors β and β_n were estimated by simulated maximum likelihood (Train 2009). Notably, the presence of random parameters allows accounting for the fact that there are multiple observations for the same decision-maker n.

Additionally, a hybrid model choice model was also specified by considering the latent variables of risk perception. The hybrid choice model integrates the latent variable of risk perception and the freight mode choice model, and it consists of structural equation of latent variable and measurement equation which relates the latent variable to observed indicators (Walker 2001). First, exploratory factor analysis retrieved the latent risk constructs and contributed to the specification of the measurement equation of the latent risk variable model. The measurement equations of the hybrid choice model expressed the distribution of the indicators as:

$$I_n = \alpha X_n^* + v_n, v_n \sim N(0, \sum\nolimits_v) \tag{4}$$

where I_n is a vector of indicators, a vector v_n of error terms following normal distribution, and a vector of fixed parameters α. In our study, the measurement I_n is reported by ordered discrete variables taking the values j_m at each Likert scale ($j_m = 1.5$) where τ_m are the parameters to be estimated. In order to account for the symmetry of the indicators, we defined two positive parameters δ_1 and δ_2 to be estimated as follows:

$$I_n = \left\{ \begin{array}{ll} j_1 & if\ X^* \leq \tau_1 \\ \mathrm{M} & \mathrm{M} \\ j_m & if\ \tau_{m-1} \leq X^* \leq \tau_m \\ \mathrm{M} & \mathrm{M} \\ j_5 & if\, \tau_4 \leq X^* \end{array} \right\} \qquad where \left\{ \begin{array}{l} \tau_1 = -\delta_1 - \delta_2 \\ \tau_2 = -\delta_1 \\ \tau_3 = \delta_1 \\ \tau_4 = \delta_1 + \delta_2 \end{array} \right. \tag{5}$$

Then, the probability of a given response j_m was obtained by an Order Probit model as:

$$P(I_n = j_m) = P(\tau_{m-1} < I_n \leq \tau_m) = \phi_v(\tau_m) - \phi_v(\tau_{m-1}) \tag{6}$$

where Φ_v is the cumulative distribution function of the error term v.

Second, the structural equation of the latent variable expressed the distributions of the latent variable X^*_n based on the observable individual characteristics X_n, a vector of error terms ω_n normally distributed with covariance Σ_ω, and a vector λ of parameters.

$$X_n^* = \lambda X_n + \omega_n, \omega_n \sim N(0, \sum\nolimits_\omega) \tag{7}$$

Third, the mode choice model specification assumed that the coefficients of some observed variables (cost and delay) vary with the latent risk variable. For example, the coefficient of delay (Z_{ni} = delay) interacted with the latent variable of internal risk (X^*_n = internal risk) as:

$$U_n = \beta X_n + \beta_n Z_{ni} \exp(\beta^* X_n^*) + \varepsilon_{ni} \tag{8}$$

Other model specifications (i.e. inclusion of other attributes) were tested but did not result in significant parameter estimates.

In the presence of latent variables, the joint probability of observing mode choice and latent variable indicators is obtained by integrating over the distribution of the latent variable and random parameters (Walker 2001):

$$\begin{aligned} &P(y_{ni}, I_n | X_n, Z_{ni}; \beta, \beta_n, \beta^*, \lambda, \alpha, \Sigma_\varepsilon, \Sigma_\omega, \Sigma_v) = \\ &\int_{\beta_n} \int_{X^*_n} P(y_{ni} | X_n, X^*_n, Z_{ni}; \beta, \beta_n, \beta^*, \Sigma_\varepsilon) f_{X_n^*}(X^*_n | X_n; \lambda, \Sigma_\omega) f_{I_n}(I_n | X^*_n; \alpha, \Sigma_v) dX^*_n d\beta_n \end{aligned} \tag{9}$$

where $f_{X_n^*}$ is the distribution of the latent variables, and f_{I_n} is the distribution of the indicators.

The simultaneous estimation of structural and measurement equations was performed. The full information estimation of the parameters enabled us to address the issue of endogeneity. Different model specifications were tested (e.g. inclusion of other variables) where the significance of parameters allowed to identify the elements of the vectors β of fixed parameters and β_n of random parameters. Moreover, a latent class model was estimated to look for non-attendance of attributes. Given the probability π_{nc} of decision-maker n belonging to class c, and given a probability $P_{ni|c}$ (expressed as eq. 3) of decision-maker n choosing mode i conditional on being in class c, the probability P_{ni} is equal to:

$$P_{ni} = \sum_{c=1}^{C} \pi_{nc} P_{ni|c} \tag{10}$$

where C is the number of latent classes. If a situation arises in which some decision-makers ignored certain attributes, it is possible to specify the latent class model so that the utility functions of some classes do not contain the attributes that are not attended. Notably, for K attributes treated in this way, there are 2^K classes covering all the combinations of attendance vs non-attendance.

5. Results

The administration of the survey to the 348 companies resulted in 86 responses (24% response rate), and 64 of these responses were complete and could be used for model estimation. Accordingly, 1,024 observations (64 times, 16 choice sets) were considered for model estimation.

Most of the respondents (69%) were shippers (31% were freight-forwarders) working in manufacturing (27%), automobile (18%), primary producers (16%), mining (14%), wholesale trade (11%), retail trade (7%), and other sectors (7%). Most companies in the sample (45%) were large (200 or more employees), 28% were medium size (20–199 employees), and the remaining 27% were small (1–19 employees). Only 6% of the companies in the sample operate exclusively in Queensland, with 27% also in New South Wales, 58% nationally and 9% globally. Most companies had previous experience with coastal shipping (83%) and were located within 25 km from a port (either Port of Brisbane or Port of Townsville). The respondents were mostly male (92%), with 22% having senior or executive roles, 25% having operational management roles, and 53% having middle managerial roles.

By using a dummy variable for shippers, it was tested whether the preference structure differed between shippers and freight forwarders. Different interactions of this dummy variable with the cost and time variables were also tested. Since the parameter estimates associated with the dummy variable was not significant, it was concluded that there is no difference in the preferences of the respondents in the two sub-samples.

5.1. Model estimates

Overall, 29.8% of the sample observations chose sea transport, with a majority (55.1%) choosing rail transport and the remaining minority choosing road transport in the hypothetical choice tasks presented to them. It is worth mentioning that this percentage is solely based on the choice tasks and may not indicate the choice preference percentages of any. Interestingly, the percentage of sea transport choices is approximately the same in the two scenarios, while the percentage of road transport halves in the road usage charge scenario.

We followed a step-wise approach where the variables were added and tested one by one and retained in the model if they were statistically significant at 95%. We hypothesised that, alongside the mode attributes, some cognitive behaviors may exist such as inertia in choosing one particular mode or the existence of prospect theory where individuals treat the increase in the variable differently from a decrease.

Table 3 presents the best model specification of four alternative models where parameters were significant at least at the 95% confidence level. The relative parameters were estimated, and the significance of the parameters revealed that they were all fixed except for the two constants that

Table 3. Estimation Results for Mixed Logit Models.

Variables	Model 1: MXL		Model 2: MXL with inertia		Model 3: MXL with asymmetry		Model 4: MXL with latent variable (hybrid choice model)	
	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio
Road transport mode								
Mean value of constant, $\beta_{road,constant}$ (*mean*)*	–	–	3.840	3.40	–	–	0	–
Standard deviation of constant, $\beta_{road,constant}$ (*st. dev.*)*	5.010	6.87	4.460	6.16	4.960	7.29	−4.600	−4.72
Toll (road usage charge), $\beta_{road,Toll}$	−1.320	−2.59	−1.300	−2.62	−1.300	−2.57	−1.400	−2.73
Operational manager, $\beta_{road,operman}$	−3.030	−3.39	−3.750	−3.68	−2.990	−3.44	–	–
Transportation of meat products, $\beta_{road,meat}$	5.680	5.02	3.450	3.14	5.670	5.39	2.960	1.98
Transportation of construction products, $\beta_{road,constr}$	2.100	2.86	–	–	2.120	2.91	1.940	1.46
Inertia, $\beta_{road,inertia}$	n/a	n/a	−0.320	−2.55	n/a	n/a	n/a	n/a
Rail transport mode								
Mean value of constant, $\beta_{rail,constant}$ (*mean*)*	1.860	3.79	2.090	3.40	1.830	3.80	1.730	3.94
Standard deviation of constant, $\beta_{rail,constant}$ (*st. dev.*)*	1.070	5.01	4.460	6.16	1.080	5.00	−0.667	−2.29
Coastal shipping								
Previous experience with coastal shipping, $\beta_{sea,exper}$	1.040	2.11	1.280	2.08	1.030	2.08	0.828	1.78
Generic mode attributes								
Travel time, β_{time}	−0.035	−6.55	−0.036	−4.39	–	–	−0.038	−5.31
Cost of mode, β_{cost}	−1.770	−6.74	−1.790	−6.60	–	–	n/a	n/a
Decrease in cost compared to sea mode, $\beta_{costdecrease}$	n/a	n/a	n/a	n/a	2.070	4.40	n/a	n/a
Increase in cost compared to sea mode, $\beta_{costincrease}$	n/a	n/a	n/a	n/a	−1.710	−6.62	n/a	n/a
Decrease in time compared to sea mode, $\beta_{timedecrease}$	n/a	n/a	n/a	n/a	0.032	3.07	n/a	n/a
Increase in time compared to sea mode, $\beta_{timeincrease}$	n/a	n/a	n/a	n/a	−0.042	−3.29	n/a	n/a
Cost of mode in interaction with market risk	n/a	n/a	n/a	n/a	n/a	n/a	−2.770	−4.73
Cost of mode in interaction with immediate risk	n/a	n/a	n/a	n/a	n/a	n/a	−2.160	−3.41
Delay of mode in interaction with internal risk	n/a	n/a	n/a	n/a	n/a	n/a	−0.019	−1.89
Number of parameters	10		11		12		50	
Null LL (mode choice model)	−1124.98		−1124.98		−1124.98		−1124.98	
Final LL (mode choice model)	−626.46		−626.53		−625.70		−647.254	
AIC	1272.92		1275.05		1275.40		1394.508	
Adjusted ρ^2	0.434		0.433		0.433		0.380	

* Normal distribution. '–' not statistically significant different from zero at the 90% level of confidence and removed. 'n/a' = not applicable.

were normally distributed. Similarly, the scale did not show the presence of heterogeneity either. All the estimations were performed in PythonBiogeme (Bierlaire 2016).

Model 2 examined whether inertia in the responses existed in that the decision-makers repeated the same choice. The existence of inertia has been frequently considered in the literature by including a dummy variable indicating the previous choice. Inertia was expressed as the habit of repeating the same choice on the basis of the previous choices:

$$Inertia_{n,i} = \sum_{t=1,16} h_{nit} \tag{11}$$

where h_{nit} is equal to 1 if mode i is chosen by the decision-maker n in the previous choice tasks t and 0 otherwise.

Model 3 attempted a better understanding of attribute processing strategies by estimating an asymmetric utility function that modelled the differences of attributes rather than their absolute values (Hess, Rose, and Hensher 2008). Accordingly, separate parameters were estimated for increases and decreases in cost and time:

$$\begin{aligned}V_{n,road} = {} & \beta_{road,constant} + \beta_{\cos tincrease}\max(Cost_{n,road} - Cost_{n,sea}, 0) + \\ & + \beta_{\cos tdecrease}\max(Cost_{n,sea} - Cost_{n,road}, 0) \\ & + \beta_{timeincrease}\max(Time_{n,road} - Time_{n,sea}, 0) \\ & + \beta_{timedecrease}\max(Time_{n,sea} - Time_{n,road}, 0) + \beta_{road,toll}Toll + \beta_{road,meat}Meat_n \\ & + \beta_{road,constr}Constr_n + \beta_{road,operman}OperMan_n + \beta_{road,inertia}Inertia_{n,road}\end{aligned} \tag{12a}$$

$$\begin{aligned}V_{n,rail} = {} & \beta_{rail,constant} + \beta_{\cos tincrease}\max(Cost_{n,rail} - Cost_{n,sea}, 0) + \\ & + \beta_{\cos tdecrease}\max(Cost_{n,sea} - Cost_{n,rail}, 0) \\ & + \beta_{timeincrease}\max(Time_{n,rail} - Time_{n,sea}, 0) \\ & + \beta_{timedecrease}\max(Time_{n,sea} - Time_{n,rail}, 0)\end{aligned} \tag{12b}$$

$$V_{n,sea} = \beta_{sea,exper}Exper_n \tag{12c}$$

Model 4 attempted a better understanding of the impacts of risk factors in mode choice by estimating a hybrid choice model. The hybrid choice model was specified with measurement and structural equations of the latent variables, jointly with the structural equation of the mode choice model. The structural equation of the choice model associates utilities of freight mode with latent variables of risk as perceived by individual n:

$$\begin{aligned}V_{n,road} = {} & \beta_{road,constant} + \beta_{cost,market}Cost_{n,road}market_n + \beta_{cost,immediate}Cost_{n,road}immediate_n \\ & + \beta_{time}Time_{n,road} + \beta_{road,toll}Toll + \beta_{delay,internal}delay_{n,road}\exp(internal_n) + \beta_{road,meat}Meat_n \\ & + \beta_{road,constr}Constr_n\end{aligned} \tag{13a}$$

$$\begin{aligned}V_{n,rail} = {} & \beta_{rail,constant} + \beta_{time}Time_{n,rail} + \beta_{cost,market}Cost_{n,rail}market_n \\ & + \beta_{cost,immediate}Cost_{n,rail}immediate_n + \beta_{delay,internal}delay_{n,rail}\exp(internal_n)\end{aligned} \tag{13b}$$

$$\begin{aligned}V_{n,sea} = {} & \beta_{time}Time_{n,sea} + \beta_{sea,exper}Exper_n + \beta_{cost,market}Cost_{n,sea}market_n \\ & + \beta_{cost,immediate}Cost_{n,sea}immediate_n + \beta_{delay,internal}delay_{n,sea}\exp(internal_n)\end{aligned} \tag{13c}$$

where $delay_{ni}$ and $cost_{ni}$ as the delay and cost of mode i respectively are modelled in interaction with the latent variables of *immediate*, *internal* and *market* risks.

Estimates for Model 1 (see Table 3) show the expected negative sign for cost and time and indicate that a road user charge would be effective in diminishing the probability of choosing road transport. Notably, the parameters are generic after no statistically significant difference emerged when estimating alternative specific parameters for any of the variables. Interestingly, frequency and level of delay were not significantly related to the likelihood of choosing any of the transport modes. When considering the characteristics of the respondents and the companies, operation management roles are related to a negative preference for road transport, while companies transporting meat and construction products are more likely to choose road transport. Expectedly, previous experience with coastal shipping increases the probability of choosing sea transport along the corridor.

Estimates for Model 2 lead to similar conclusions, but also suggest that inertia is present, although with a different sign than expected. In fact, it appears that choosing road transport translates in a lower probability to repeat the choice in following tasks.

Estimates for Model 3 present similar results for what concerns the sensitivity to toll, being an operation manager, and transporting meat or construction products. The estimates for the asymmetry in the utility function reveal that the asymptotic t-ratios of the differences between $\beta_{costincrease}$ and $\beta_{costdecrease}$ (t-ratio = 0.50) and between $\beta_{timeincrease}$ and $\beta_{timedecrease}$ (t-ratio = 0.88) are low, thus indicating that the response to increases and decreases is actually symmetrical. The lack of asymmetry is along with other results from tests during the estimation process, as tests revealed the absence of reference point revision effect (Masiero and Hensher 2010), namely decision-makers did not adjust their preferences gradually during the choice tasks by keeping the previous choice as a reference point, plausibility effect (Hensher and Collins 2011), namely decision-makers did not choose always an alternative that outperformed the others in a specific attribute), and regret minimization behaviour (Chorus, Rose, and Hensher 2013), namely regret terms were not significant and did not perform better than utility models.

Estimates for Model 4 illustrate similar conclusions, but also suggest that delay and cost relate to the mode choice in interaction with risks. The mean value of latent variables of *internal risk* and *immediate risks* in interaction with the cost of transport resulted in less standard errors compared with the model without a latent variable. It was also the case for the interaction of *market risk* and delay where delay did not turn out to be significant in the model in the absence of the latent variable. Given that the risk factors were only significant in an interaction with delay and cost, we hypothesized that the risk latent variable does not directly relate to the mode choice but has an indirect relation where cost and delay are perceived differently according to different levels of risk. Notably, the hybrid model offered greater explanatory power by decomposing the influence of observable variables attributed to risk factors.

Table 4 presents the estimates of the measurement equations and the structural equations relating to three latent risk variables. Considering the estimates of latent variable models, females and senior respondents had a higher perception of risk. A higher proportion of owned fleets to leased fleets also led to a higher perception of risk. The estimates showed that a higher number of long-term contracts increased the perception of internal risks. Also, larger shippers, and operational and executive managers perceived higher risk regarding the competition in the market. It should be noted that the serial correlation between three latent variables as well as the choices was examined such that an error component appeared in all the structural equations of latent variable models and choice model, distributed across the respondents. However, this correlation was not verified by the non-significant estimated parameter, meaning that the latent variables and choice model do not share an unobserved variable specific to the respondents. The constant of the latent variable *market* also was not statistically significant; hence, it was constrained to zero. In this sample, no difference in the preference and risk structure was found across freight forwarders and shippers since the estimate of the parameter associated with the dummy variable for shippers was not statistically significant.

The estimation of the latent class model allowed us to verify whether there existed attributes that were ignored while choosing among the alternative modes and hence were non-attended (Hensher, Rose, and Greene 2005). Specifically, a latent class model was estimated initially with four classes for two parameters, and then successive tests revealed that a model with five classes provided a better fit with the data (Table 5). The five classes included the first two classes with both attributes, the third class with non-attended time, the fourth class with non-attended cost, and the fifth class with both non-attended attributes. Table 6 presents the non-attendance with latent variables, where non-significant parameters are omitted from the model.

In the absence of the latent variables, the estimates of the latent class model (Table 5) showed an improvement over the three models (Models 1–3), as the comparison with Model 2 is better in terms of AIC (1,229.56 vs. 1,272.92) and ρ^2 (0.454 vs. 0.433). This result is consistent with the result of a study by Kim et al. (2018) in terms of the presence of classes within freight long-hauliers with distinct preferences. Most relevantly, the model estimates reveal that on average there was a probability of 49.1% that respondents in the sample considered both cost and time, 25.9% that they ignored time, 10.9% that they ignored cost, and 14.1% that they ignored both attributes in their

Table 4. Estimates of the measurement and structural equations of the latent variable model.

	Estimates	t-ratio
Measurement equations		
Internal risk		
Injury to workers	1.000	n/a
Environmental impact of business operations	1.040	3.80
Failure to attract or retain top talent	0.331	1.57
Lack of corporate social responsibility/sustainability	1.090	3.23
Lack of confidentiality of information (e.g. due to computer crime, and hacking)	0.460	1.75
Market risk		
Damage to reputation/brand	1.000	n/a
Increasing competition	0.330	4.36
Failure to innovate/meet customers' demand	0.520	5.25
Disruption or logistics chain failure	0.756	5.23
Merger/acquisitions/restructuring	0.390	2.15
Immediate risk		
Change to logistics operations	1.000	n/a
Property damage	0.459	2.83
Structural equations		
Internal risk		
Constant	0.119	3.07
Having a contract with more than ten providers and over the long term	2.310	4.48
Age over 50 years old	0.537	1.71
The proportion of owned fleet to the leased fleets	0.744	1.96
Market risk		
Operational or executive managers	0.149	5.01
Female	0.263	7.19
Shipper with more than 20 employees	0.239	1.68
The proportion of owned fleet to the leased fleets	0.457	2.58
Age over 40 years old	0.480	2.23
Immediate risk		
Constant	−0.974	−2.29
Female	0.753	1.62
The proportion of owned fleet to the leased fleets	1.190	4.77
Age over 40 years old	0.714	3.05

For conciseness, the estimates of constants in the measurement equation and standard deviations are excluded from this table and are outlined in Appendix. 'n/a' = not applicable.

choice. Anecdotes from the Australian freight transport industry confirm this result where transport mode familiarity, flexibility, and fixed or long-term transport contracts are other influential factors in the mode choice where travel time and cost may not necessarily be taken into account. This result suggests that while travel time and cost for some commodities and contractual arrangements might matter, these attributes might be less relevant or even not relevant at all for some other shipments and transport contractual types.

Notably, dropping the non-significant time attribute in the fourth class did not outperform the results in terms of goodness of fit. The estimation revealed similar sensitivity to cost in the three classes where cost was considered, and different sensitivity to time in the three classes where time was not ignored. In all classes, previous experience with coastal shipping related positively to the choice of sea transport, and road usage charges associated negatively with the choice of road transport.

5.2. Elasticity and demand response

Aggregate elasticity measures were calculated by using the Probability Weighted Sample Enumeration:

Table 5. Estimates of the attribute non-attendance model.

Variables	Class 1 mean	Class 1 t-ratio	Class 2 mean	Class 2 t-ratio	Class 3 mean	Class 3 t-ratio	Class 4 mean	Class 4 t-ratio	Class 5 mean	Class 5 t-ratio
Road transport mode										
Constant	0.879	1.47	0.879	1.47	−6.169	0.00	87.40	0.00	**1.358**	**3.83**
Toll (road usage charge)	−1.361	−1.49	−1.361	−1.49	−0.58	0.00	−0.564	−0.37	−2.633	−1.39
Operational manager	−0.917	−1.56	−0.917	−1.56	−0.917	−1.56	−.917	−1.56	−0.917	−1.56
Transportation of meat products	1.969	0.90	1.969	0.90	−0.742	0.00	**−1.602**	**−3.01**	0.671	0.03
Transportation of construction material	**2.309**	**4.19**	**2.309**	**4.19**	−2.479	0.00	81.124	0.00	1.473	1.38
Shippers with 1–19 employees	**1.314**	**1.67**	**1.314**	**1.67**	0.139	0.00	**1.314**	**1.67**	−0.639	−0.72
Rail transport mode										
Constant	**1.957**	**7.09**	**1.957**	**7.09**	**2.265**	**4.14**	87.01	0.00	**1.251**	**2.99**
Coastal shipping										
Previous experience with coastal shipping	**0.959**	**3.15**	**0.959**	**3.15**	**0.959**	**3.15**	88.544	0.00	**0.959**	**3.15**
Generic mode attributes										
Travel time	**−0.128**	**−3.41**	**−0.057**	**−4.74**	–	–	−0.140	−1.25	–	–
Cost of mode	**−0.004**	**−4.97**	**−0.001**	**−5.87**	**−0.006**	**−5.89**	–	–	–	–
Class probability	**0.161**	**n/a**	**0.329**	**3.63**	**0.259**	**2.83**	**0.109**	**2.51**	**0.141**	**2.56**
Number of parameters					50					
Null LL					−1124.98					
LL					−564.78					
AIC					1229.560					
Adjusted ρ^2					0.454					

'–' not statistically significant different from zero at the 90% level of confidence and removed. 'n/a' = not applicable. Bold numbers are statistically significant at 90% of confidence level.

Table 6. Elasticity.

Attributes	Elasticity for road transport	Elasticity for rail transport	Elasticity for sea transport
Direct elasticity			
Cost	−2.508	−1.208	−1.709
Time	−0.261	−0.481	−0.835
Toll	−0.024	-	-
Cross elasticity			
Cost of road	-	0.496	0.403
Cost of rail	0.911	-	1.754
Cost of sea mode	0.329	0.831	-
Time of road	-	0.049	0.045
Time of rail	0.348	-	0.707
Time of sea mode	0.169	0.404	-
Toll of road	-	0.018	0.008

$$\bar{E}_{x_i}^{P_i} = \frac{\sum_n E_{x_i}^{P_{ni}} P_{ni}}{\sum_n P_{ni}} \tag{14}$$

where $\bar{E}_{xi}^{Pi}$ is the elasticity that measures the percentage change in the probability P_{ni} of decision-maker n choosing mode i with respect to a given percentage change in an attribute x_i (direct elasticity), or the probability P_{nj} of decision-maker n choosing mode $j \neq i$ with respect to the same percentage change (cross elasticity).

Table 6 presents the elasticity measures for Model 2. When looking at direct elasticity, road transport is more elastic when compared to rail and sea with respect to a 1% increase in cost, while the sea is more elastic than rail and road with respect to a 1% increase in time. The elasticity effect of the toll on road transport is quite small. Transport cost seems to be the most elastic attribute in the mode choice in this corridor. An increase in the road transport cost by 1% could decrease up to 2.5% of the market share of this mode. When looking at cross elasticity, the most sensitive is the increase of the probability of choosing sea transport by 1.75% with respect to a 1% growth of transport cost by rail, and by 0.71% with respect to a 1% growth of transport time with rail. Again, introducing a toll has a small effect on mode shift. It should be noted that, although the percentages appear small, the variations might be quite substantial when thinking for example, that the difference in attribute levels is about 50% to 100% in transit time.

5.3. Willingness to pay

Willingness to pay (WTP) was calculated in terms of the amount of money that decision-makers were willing to pay to save a unit of time. Given the linear-in-parameters specification, the WTP was simply the ratio of the time parameters to the cost parameter (Train 2009).

When considering Model 2 in Table 3, the Delta method was computed to take into account that both time and cost parameters were estimated with a sample variance. The derived WTP was 19.44 AUD/hour, with a 95% confidence interval between 14.18 and 25.04 AUD/hour. Namely, on average the decision-makers would be likely to pay 19.44 AUD to decrease the transit time of the freight transported on the corridor by one hour.

When considering the latent class model in Table 5, the WTP was computed for the first two classes that ignored neither the time nor the cost. Intuitively, the averaging from the posterior weighted probabilities does not provide any insight (as some classes do not have either the numerator, or the denominator, or both for the calculation of the WTP), and hence the Delta method was used for each class, and the standard error was calculated as follows:

$$S.E.\left(\frac{\beta_{time,c}}{\beta_{\cos t,c}}\right) = \sqrt{\frac{1}{\beta_{\cos t,c}{}^{2}}\left[\mathrm{var}(\beta_{time,c}) - \frac{2\beta_{time,c}}{\beta_{\cos t,c}}\mathrm{cov}(\beta_{time,c},\beta_{\cos t,c}) + \left(\frac{\beta_{time,c}}{\beta_{\cos t,c}}\right)^{2}\mathrm{var}(\beta_{time,c})\right]} \tag{15}$$

The WTP for class 1 was 30.77 AUD/h, with a 95% confidence interval between 11.25 and 50.28 AUD/h. The WTP for class 2 was higher and equal to 44.22 AUD/h, with a 95% confidence interval between 16.18 and 72.25 AUD/h.

Clearly, considering non-attendance provides a larger confidence interval and on average a higher WTP. The average values are comparable to the values from the aggregate analysis of three corridors in Australia (Brooks et al. 2012), where the WTP had a mean value of 23.09 AUD/hour which is included in all three aforementioned confidence intervals. A higher value was found on a European corridor (Arencibia et al. 2015), where the WTP had a mean value of 20.79 EUR/hour (at the time, about 30.15 AUD/hour) and a median value of 17.24 EUR/hour (at the time, about 25.00 AUD/hour.

6. Policy implications

The estimation results in the previous section provide insight into the significant mode attributes and freight characteristics. However, for policy implications, it would be useful to simulate the impact of these variables by estimating the average treatment effects (ATEs). The ATE metric computes the impacts on a downstream posterior variable of interest due to a treatment that changes the state of an antecedent variable from a base to a treatment level. The mean of the aggregate-level ATEs is computed across 1000 bootstrap draws taken from the estimated sampling distributions of the model parameters, as follows:

Table 7. Overall ATEs of variables on mode choice.

Variables	Base	Treatment	Road	Rail	Coastal
Previous experience with coastal shipping	No	Yes	−0.012	−0.110	0.122
Toll (road usage charge)	No	Yes	−0.049	0.034	0.016
Cost of road transport	1,000 AUD	5,000 AUD	−0.417	0.275	0.143
Cost of rail transport	1,000 AUD	5,000 AUD	0.147	−0.784	0.637
Cost of coastal shipping	1,000 AUD	5,000 AUD	0.069	0.602	−0.672
Road travel time	19 Hours	72 Hours	−0.065	0.044	0.021
Rail travel time	19 Hours	72 Hours	0.050	−0.250	0.199
Sea travel time	19 Hours	72 Hours	0.027	0.228	−0.255
Transportation of construction products	Yes	No	−0.086	0.058	0.028
Transportation of meat products	Yes	No	−0.292	0.194	0.097
Operational manager	Yes	No	0.099	−0.067	−0.031

$$ATE_i = \frac{1}{N}\sum\nolimits_n [P(y_{ni} = 1|a_{nt} = 1) - P(y_{ni} = 1|a_{nb} = 1)] \quad (16)$$

where a_{nt} is the dummy variable for the category t *(i.e. treatment)* of the determinant variable for the individual n, a_{nb} stands for the dummy variable for the category b *(i.e. base)* of the determinant variable for the individual n, y_{ni} is the choice indicator. Thus, ATE_i represents the estimate of the expected value change in the mode choice outcome i because of a change from the base category b to treatment category t of the determinant variable.

Table 7 presents the ATEs for Model 1 since that constitutes the outcome of a simpler model which could be of policymakers' interest. For presentation ease, we only report the ATEs for a change from the lowest extreme to the highest extreme for the antecedent variable.

Overall ATEs indicate that if 100 freight agents who do not have previous experience with coastal shipping were replaced by 100 people familiar with this mode, 12 additional freight actors (of the 100) would choose coastal shipping mode, eleven of which would shift their mode from rail to coastal shipping. Other ATE values may similarly be interpreted. The introduction of road toll would make 3% of freight actors swap the road with the rail option and 1% swap with the coastal shipping option.

Increasing the road cost by 4,000 AUD would result in 27% of freight actors shifting their mode from road to rail and 14% from road to coastal shipping. This increase in the cost of coastal shipping, however, would lead to 60% and 7% of freight actors choosing rail and road, respectively, instead of coastal shipping. By increasing sea travel time from 19 to 72 hours, 23% of freight actors would choose rail and 3% would choose road transport. Looking at the overall ATEs, it turns out that the trade-off occurs between rail and coastal shipping, as with any changes in the attributes of one, the majority swap to another instead of road transport.

A change in transporting construction and meat products to other commodities leads to an ATE effect decrease in road transport. For transporting non-construction products, about 6% and 2% would choose rail and sea mode, respectively. While for transporting non-meat products, about 19% and 10% choose rail and sea mode, respectively. Also, if the transport mode were to be chosen by the higher levels of management (i.e. executive and middle managers), 7% would choose road instead of rail and 3% would choose road instead of sea mode.

7. Discussion and conclusions

This study aimed at investigating the demand for coastal non-bulk freight shipping in Queensland and found that there is indeed a potential demand for the sea freight mode. This finding is supported by about 30% of the choices in the discrete choice experiment among shippers and freight-forwarders made for sea transport. The rail mode was the most preferred by respondents. This finding is partially in line with findings by Brooks et al.

(2012) who found that respondents showed a general preference for rail and road freight modes in the Australian context. The application of the model revealed relatively low elasticity in terms of potential percentage changes in mode choice, given the selected attribute characteristics. However, it should be considered that the variations in costs and transit times over the 1,300 km corridor may be substantial. The relatively low preference for the road mode contrasts with findings of other studies (e.g. Larranaga, Arellana, and Afonso Senna 2017; Feo, Espino, and García 2011) and may be explained by the specific study context.

Similarly, the non-significance of frequency and delay could also be a result of the specific sample and context. As Arencibia et al. (2015) observed in their study, the term *delay* could be misinterpreted and mixed with the meaning of on-time delivery. Hence, respondents in the present may have also struggled with the interpretation of attribute as a concept of delivery punctuality.

The results revealed that there is some potential for reducing the significant externalities from road transport (i.e. greenhouse gas emissions, road crashes and injuries, congestion in urban areas) via both, rail, and sea. Moreover, the WTP values are in line with existing evaluations for Australian freight corridors (Brooks et al. 2012) which suggests that the modelling effort produces reasonable values.

The results also suggested that there are companies that transport specific commodities (e.g. meat, construction material) with a clear preference for road transport. Operations managers appear to be more prone to choosing the road mode over rail or sea, while experience with coastal shipping seems related to choosing sea transport. A road usage charge influences modal shift, although the mere count of the choices suggests that rail would benefit rather more than coastal shipping. Moreover, two behavioral elements emerged from the model results: (i) inertia appears not to exist for road choices initially, but it is negatively related to repeating the road transport choice; (ii) non-attendance for cost and/or time is present in the sample for about half of the decision-makers, which means that either (if not both) of these attributes is likely not to be considered in the choice. Differences between findings from the sample analysis, the focus group (which considered costs and time as important) and previous literature may be explained by the context of Australian operational business models. This is supported by Mitchell and McAuley (2009), who note in the Australian context that the nature of the freight and the requirements of shippers influence the relative importance of costs and service quality (e.g. time, reliability). Furthermore, Queensland Government (2019) noted that existing and potential rail service customers on the north coastline (e.g. Brisbane-Cairns) are facing reliability issues of rail services (i.e. ongoing maintenance requirements, inability to operate longer train lengths, potential flood risks, limited path availability). These could be reasons why cost and/or time may not have been considered by some decision-makers in our sample. However, further empirical research would be required to verify this.

Furthermore, the perception of risk was taken into account by estimating a hybrid choice model. Findings suggest that freight decision-makers evaluate the cost and delay of freight mode in correspondence with risk factors. This was particularly the case for risk factors that are associated with the internal procedures of the company, completion in the freight market and immediate perceived risks.

The model results are supported by the comments provided by survey participants about the perceived advantages and disadvantages of the coastal shipping mode. It appears that some decision-makers in the sample are relatively open to exploring coastal shipping, provided that it will be reliable and cost-competitive with respect to the land-based modes when considering port-related extra handling costs. This is in line with findings by Konstantinus and Woxenius (2022), who suggest that service quality requires adjusting to make short sea shipping more viable in the context of Southern Africa. This confirms the initial assumption that a mode shift is likely only to be considered for selected logistics operators, rather than on a broader scale. While this finding somewhat contrasts results from previous studies (e.g. Brooks et al. 2012, Konstantinus and Woxenius 2022) it can be argued that the country and freight corridor context is important to consider when comparing mode choice studies. For example, current broader challenges to the freight system in specific regions (e.g. infrastructure maintenance, exposure to natural risks such as flooding and cyclones, and level of rail track competition) may explain differences in findings across empirical studies which are typically not the center of the primary analysis but may affect mode choices. The participants also mentioned the need for efficiency that would come from the integration within the supply chains of the transported commodities.

Revival of Australian-flagged coastal shipping would not only strengthen the Australian sovereignty across its coastal borders but would most likely contribute to the economic developments of regional cities and town in the north of Australia. Another substantial role of domestic coastal shipping is to diversify transport choices and to mitigate the risks of road closures due to natural incident events such as cyclones, bushfires, and floods. From a policy perspective, the competitiveness of coastal shipping mode could be increased through a regulatory change by forgoing the cabotage and thus lowering domestic labor costs (Everett and Kittel 2010). While a legislative regime can render its uncompetitive situation with its foreign competition, coastal shipping skill gaps and lack of business models may cause upheaval to this new industry. Broader social implications of such regulatory changes, e.g., fair payment of crew of foreign-flagged vessels, also need to be considered in this decision. Furthermore, as Saldanha and Gray (2002) argued, a favorable legislation will likely not be effective if it does not result in subsequent action from the logistics industry in Queensland. Hence, it will be important for the industry and the government to mutually explore an enabling environment for coastal shipping to further emerge in Queensland. This may include the development of marketing strategies that promote the competitive advantage of choosing this mode.

Limitations of this study include the usual caveats related to SP studies (e.g. framing bias, social desirability bias, cognitive burden) and potential concerns about the representativeness of the sample given the relatively small number of responses to the survey. Furthermore, the relatively strong representation of middle management roles (53%) in the sample may affect the results since executive managers may have made different choices.

Further research could examine whether other factors could affect the choices, in particular traits of the companies such as risk aversion towards logistic operations or adverse weather conditions that affect at times the corridor. Also, further research could address whether there would be the risk of empty travel in the case that the demand was not balanced in the two directions.

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Appendix

Estimates of the constants and standard deviations of measurement equations of hybrid model

	Estimates	t-ratio
Measurement equations		
Internal risk indicators		
Constant of injury to workers	0.000	n/a
Constant of environmental impact of business operations	−0.270	−1.87
Constant of failure to attract or retain top talent	0.000	0.00
Constant of lack of corporate social responsibility/sustainability	−0.380	−2.78
Constant of lack of confidentiality of information	–	–
Standard deviation of injury to workers	0.000	n/a
Standard deviation of environmental impact of business operations	0.870	9.01
Standard deviation of failure to attract or retain top talent indicator	0.776	10.18
Standard deviation of lack of corporate social responsibility/sustainability	0.746	9.63
Standard deviation of lack of confidentiality of information	0.938	7.74
Market risk indicators		
Constant of damage to reputation/brand	0.000	n/a
Constant of increasing competition	–	–
Constant of failure to innovate/meet customers' demand	–	–
Constant of disruption or logistics chain failure	–	–
Constant of merger/acquisitions/restructuring	−0.332	−2.89
Standard deviation of damage to reputation/brand	0.000	n/a
Standard deviation of increasing competition	−0.438	−7.50
Standard deviation of failure to innovate/meet customers' demand	−0.416	−7.67
Standard deviation of disruption or logistics chain failure	0.770	8.91
Standard deviation of merger/acquisitions/restructuring	−0.378	−6.49
Immediate risk indicators		
Constant of change to logistics operations	0.000	n/a
Constant of property damage	−0.326	−2.91
Standard deviation of change to logistics operations	0.000	n/a
Standard deviation of property damage	0.835	8.21

Notes: '–' not statistically significant different from zero at the 90% level of confidence and removed. 'n/a' = not applicable.