FREIGHT MARKET INTERACTIONS SIMULATION (FREMIS): AN AGENT-BASED MODELLING FRAMEWORK

by

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Graduate Department of Civil Engineering
University of Toronto

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Abstract

Freight transport is the output of an economic market, which converts commodity flows into vehicle flows. Interactions in this market influence vehicle flows and since freight market characteristics (product differentiation and economies of scale/scope) violate perfect competition conditions, the output of this market cannot be predicted directly, unless these interactions are represented in the forecasting models. Traditional freight modelling frameworks do not consider these interactions and consequently they may provide inaccurate freight flow forecasts. In this dissertation, a freight modelling framework is proposed using simulation of freight agent interactions in the economic market to forecast freight flows. The framework is named FREMIS (FREight Market Interactions Simulation). The FREMIS framework consists of two demand models to represent shipper decisions (bundling of shipments and carrier selection) in the market and functions based on profit maximizing behaviour to simulate carrier proposals for contracts. Besides that, learning models are proposed to simulate agent learning processes based on their interactions. The framework was developed aiming to create a realistic representation of freight markets using feasible data collection methods. To illustrate the feasibility of the data collection, a customized web survey was implemented with shippers and carriers in a freight market. Two
probabilistic models were developed using the data. The first model, a shipment bundling model was proposed combining a probabilistic model and a vehicle routing algorithm. The results of the probabilistic model are presented in this dissertation, where the locations of shipments (origin and destination) influence the probability of bundling them. Second, three carrier selection models were developed aiming to analyse the nonresponse bias and non-attendance problem in the survey. All of these models assumed heteroskedasticity (different scale or variance) in shipper behaviour. In all models, the hypothesis of agents’ heteroskedasticity cannot be rejected. Besides that, nonresponse bias and non-attendance problem were identified in the survey. In conclusion, the models obtained from the survey were consistent with their behavioural assumptions and therefore they can be adopted during FREMIS implementation.
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Dedication

To my beloved Paola.
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Chapter 1

Introduction

Imagine how hard physics would be if electrons could think.
Murray Gell-Man

A market is a place where the exchange of resources, products or services happens between buyers and sellers. Freight transport is the provision of a service and it is an output of the interactions of two markets\(^2\) (see Figure 1.1): a commodity market and a freight market. In a commodity market, producers (vendors) sell commodities/products to receivers (buyers) and receive resources in exchange. After a transaction is established, a list of shipments (commodity flows) is forwarded to a shipper who is responsible for arranging logistics services for them (Roorda, et al. 2010). A shipper can be a department in the producer or in the receiver company, or a third party logistics provider.

---

1 1969 Nobel laureate in physics
2 In the literature, sometimes freight markets include commodity markets. This research adopts the same market structure used in Roorda et al. (2010)
Logistics services are exchanged in a freight market where logistics services providers, or carriers, offer these services and shippers contract them. The input of the freight market is composed of sets of shipments, which can be represented by commodity flow matrices. The transactions in a freight market assign commodity flows to different carriers who use vehicles to provide the services contracted. The final output is a set of vehicle flows. These vehicle flows can be represented by vehicle flow matrices, see Figure 1.2. Therefore, any freight market simulation can be understood as a procedure to represent the conversion of commodity matrices into vehicle matrices. In addition to that, it has to provide mechanisms to represent the interactions between commodity and transportation markets.

Commodity markets, freight markets, and freight transport are part of a large and complex system: the supply chain system. This system is composed of all agents who are involved in the transformation of raw materials into finished products, which are bought by end-consumers (Simchi-Levi, et al., 2003). This system is very diverse and interconnected with subsystems for distinctive products (Bäckstrand, 2007) and a single product may have many levels (e.g. suppliers, retailers) organized in different configurations. For instance, Feng and Chern (2009)
identified four main supply chain configurations in the notebook industry, and these configurations are changing constantly since they are one important element in companies’ competitive strategy (Simchi-Levi, et al., 2003).

![Figure 1.2: Freight Market: Input and Output](image)

Freight transport is represented by the movement of different vehicles e.g. trucks, ships, trains, vans, and others. The analysis and study of these flows are the main elements in freight transportation planning (Cambridge Systematics, 1996 and 2007). Since these flows are the output of economic markets, a representation of commodity markets and freight markets with their agent interactions (e.g. transactions) will seemingly result in better forecast of these flows and, consequently, in an improvement in the evaluation of freight-related policies in transportation planning.

This dissertation focuses on the development of a comprehensive framework to simulate freight market interactions. Although a simpler case than the simulation of commodity markets (Simchi-Levi, et al., 2003), there are still many obstacles in obtaining an accurate representation of interactions in freight markets. Major obstacles are related to some characteristics of freight markets, which violate competitive equilibrium conditions (Anderson et al., 1992), such as product differentiation (e.g. Winston, 1983) and economies of scope or scale (e.g. Clarke and Wright, 1964; Sheffi, 2004; Jara-Díaz, 2000).

Product differentiation exists in a market if consumers assign a diverse value for distinctive products (Anderson et al., 1992). This is a characteristic of freight markets. For instance, freight mode choice is based on multiple attributes such as freight rate, time reliability and loss/damage
of products. This result has been empirically validated by several studies (Winston, 1983; McFadden et al., 1985; Evans et al., 1990; Fowkes, 2007; Meixell and Norbis, 2008; Patterson et al., 2010). The existence of product differentiation has become usual in many economic markets (Anderson et al., 1992), which ultimately influences company strategies (Porter, 1980).

Economies of scope and scale are advantages in cost savings that companies have when providing an additional service or product (Tirole, 1988). According to Jara-Díaz and Basso (2003, p. 283): “scale economies are related to the convenience or inconvenience of expanding proportionally the flows in all OD pairs, while economies of scope are related to the potential advantages or disadvantages of serving all OD pairs with one firm”. In freight markets, vehicle routing problems have been studied since late 1950s with the seminal work of Dantzig and Ramser (1959). In this type of problem, economies of scope are the main motivation for the combination of shipments with different locations (origin/destination) in the same vehicle creating a tour (Clarke and Wright, 1964; Sheffi, 2004). Jara-Díaz (2000) named this type of economy of scope as economy of spatial scope.

A comprehensive framework for freight market simulation must include a market representation of product differentiation and economies of scale/scope. Another requirement for this framework is the representation of the interconnection between commodity markets and freight markets. The proposition of this framework and the collection of the important elements required for its implementation in a freight market are the main objectives of this dissertation.

### 1.1. Objective and Scope

The main objective of this dissertation is the development of a modelling framework for the simulation of interactions in freight markets. The framework is formulated to permit its application in freight markets with any geographical scope (international, intercity, or urban). Its principal intention is to represent the aggregate behaviour of the market under study (see Figure 1.2). This framework is named FREMIS (FREight Market Interactions Simulation).

FREMIS specific objectives are to represent the following three relevant components in freight market using a microsimulation approach: product differentiation, economies of scope/scale and
inter-market interactions. These components are represented in the FREMIS formulation presented in Chapter 3.

The first component, product differentiation, is a characteristic of freight markets since the delivery of shipments usually requires a certain level of service (e.g. on-time delivery). This results in market power for some companies or modes (Mas-Colell et al., 1995) with a higher level of service in the freight market. The incorporation of this element into freight modelling will permit the direct evaluation of the impact of new types of modes since their demand is a function of their level of service (Patterson et al., 2010). One clear example of this market power in freight is the higher preference for motor freight carriers in urban freight movements (Cambridge Systematics, 2007).

The second component, economies of scope/scale, is also a characteristic of freight markets because shipments can be delivered using the same vehicle, resulting in lower operational costs. These economies are relevant in urban freight contexts, and some predictive demand models have been developed to incorporate them (e.g. Hunt and Stefan, 2007; Wang and Holguín-Veras, 2008 and 2009). Nevertheless, these models do not explicitly incorporate a simulation of agent interactions in the market and, consequently, they are not sensitive to market changes (e.g. new facilities, freight hubs).

The last component, inter-market interactions, are required in freight market simulation because commodity markets, freight markets and transport operations are interrelated. For instance, carrier operations influence their perceived level of service and costs in the freight market. As a consequence, the output of these operations impacts the transactions in the commodity market (e.g. ordering cost in the economic order quantity model associated with carriers' level of service).

The last specific objective of this dissertation is to investigate many elements required for implementation in a particular freight market, i.e. the Greater Toronto and Hamilton Area (GTHA) freight market. This investigation has the objective of demonstrating FREMIS applicability. The investigated elements are the demand models in the framework (see Chapter 3). These models are developed using data from a stated preference (SP) web-survey with
shippers and carriers (see details in Chapter 4), since data with agents’ transactions in this freight market are otherwise not available. These models are combined in FREMIS to result in a realistic simulation of the freight market. The results of these models are presented in Chapters 5 and 6.

The complete implementation of FREMIS for the GTHA freight market will still require two elements. These elements are a list of shipments from GTHA commodity market and a model to simulate freight transport operations in the GTHA region. These elements are not currently available and therefore, the full-scale implementation of the FREMIS is not part of this dissertation.

1.2. Motivation

The main motivation of this research was a question that emerged during the development of the paper presented in Roorda et al. (2010):

*How to simulate agent interactions in a freight market using a feasible data collection procedure?*

Traditional freight modelling frameworks are based on passenger approaches (Cambridge Systematics, 2007). Modelling approaches for passenger travel are usually developed using the premise that decision makers do not interact with each other (Órtuzar and Willumsen, 2011). For instance, disaggregate mode split models do not traditionally include any representation of interactions between passengers (Ben-Akiva and Lerman, 1985). Some recent modelling approaches represent interactions between passengers if they are from the same household (Miller and Roorda, 2003; Roorda et al., 2008) or if they have a social relationship (Dugundji et al., 2011).

Assuming that freight transport is the output of market agent interactions, an accurate representation of them is essential for the development of behavioural-based freight modelling frameworks. As a consequence, passenger-based approaches should not be used for freight modelling. This conclusion is not recent. Friesz et al. (1985) came to this conclusion almost 30
years ago and their paper was one of the origins of the FNEM (Freight Network Equilibrium Model). FNEM is a commercial multimodal freight network model applied for intercity freight markets, which represents the interactions between shippers and carriers using a static game-theoretical approach (Friesz, 2000; de Jong et al., 2004). The FNEM does not incorporate the components proposed in this research (product differentiation, economies of scope and inter-markets interactions), but it was a relevant contribution towards the development of specific freight modelling frameworks.

In the last 30 years, Prof. Friesz developed other freight modelling frameworks using game-theoretical approaches. Most of them have not been applied to a practical case (e.g. Friesz and Holguín-Veras, 2005) and some of them include the main elements of FREMIS. For instance, the Generalized Spatial Price Equilibrium Model - GSPEM (Harker and Friesz, 1986a, b) includes the inter-relation between commodity and freight markets, but it has only one application (Friesz, 2000).

Game-theoretical approaches use the concept of Nash equilibrium. Nash equilibrium occurs when all agents in the market are adopting a strategy that solves simultaneously their response functions (Fudenberg and Tirole, 1991). Response functions provide the strategy to maximize agent’s payoff (e.g. profit) given the strategies of other agents (Fudenberg and Tirole, 1991). Therefore, the identification of Nash equilibrium(s) in a market requires finding the solution of a system of equations (agent’s response functions). When the market is in a Nash equilibrium, agents do not have any incentive to change individually their strategies because it will result in a lower profit.

Using these approaches, simple markets (e.g. competitive markets) are feasible to model, but a complex market (e.g. commodity market or freight market) may result in unsolvable mathematical problems. Usually, simplifying assumptions are required to solve them (e.g. Friesz and Holguín-Veras, 2005). Another important issue with the direct application of these game-theoretical approaches in freight markets is the lack of disaggregate data with agent interactions. For instance, recent modelling frameworks developed by Prof. Friesz (e.g. Friesz and Holguín-Veras, 2005) are able to represent nearly all components presented in this dissertation. However,
they are still only theoretical formulations, and they require considerable data collection efforts to be fully implemented.

Some game theoretical modelling approaches can be classified as “top down” approaches. These approaches rely on the definition of equilibrium points (Nash equilibrium) assuming a homogeneous behaviour of agents to estimate disaggregate behavioural models using market data (Ehrentreich, 2008). Two main disadvantages exist in these approaches when applied for freight modelling. First, they involve advanced mathematical formulations that can only be analytically solved with simplifying assumptions. And a consequence for this, they depend heavily on the assumptions used to find the equilibrium (the “top”), which is usually difficult to define in freight markets (Friesz and Holguín-Veras, 2005).

Agent-based approaches (“bottom-up” approaches) are alternatives to game-theoretical approaches. In agent-based approaches, the main objective is to represent market agent interactions (the “bottom”) as realistically as possible and to identify equilibrium points, if they exist, as an output of market simulation experiments (Derveeuw, 2005; Ehrentreich, 2008). Some applications in other markets have already demonstrated that agent-based approaches can identify correctly Nash-equilibrium points (e.g. Deguchi, 2005; Saguan et al., 2006; Ehrentreich, 2008).

An advantage of agent-based approaches is that they can be implemented accurately for any complex market (Ehrentreich, 2008). This is a function of how realistic is the representation of agent behaviour (Ehrentreich, 2008). One disadvantage of these approaches is the calibration and validation process (Bankes, 2002). Since there are no equilibrium assumptions, it is difficult to calibrate parameters based on secondary data (e.g. traffic data, freight rates, list of companies). These data usually represent only one realization of a random variable. As a consequence, the calibration and validation process for agent-based approaches has to be specifically developed.
1.3. Approach

Both approaches, game-theoretical and agent-based, have features that permit the development of accurate freight market models. They can incorporate the three relevant components of freight markets. An agent-based approach was selected in this research because of the following advantages.

First, agent-based approaches require a simplified data collection procedure. The objective of these approaches is to represent the agent’s disaggregate behaviour and therefore data collection can focus on developing behavioural models to represent individual agents. As a consequence, more information about the market (e.g. structure, number of participants, forms of transactions, how market information is propagated) is not required (Derveeuw, 2005; Ehrentreich, 2008). Meanwhile, market information is required to identify the Nash-equilibrium point(s) in game-theoretical approaches.

Second, agent-based approaches have a higher transferability/easier customization. In game theoretical approaches, simplifying assumptions are necessary to identify the Nash equilibrium points. This is not a requirement in the agent-based approaches. These approaches can also be easily adapted / customized for applications in freight markets with distinctive characteristics.

Agent-based approaches are one type of microsimulation approach (Tesfatsion, 2006). The advantages of microsimulation models when applied to freight demand forecasts have been identified almost 15 years ago (the first application was Boerkamps et al., 2000). Most of these freight models do not have a representation of market dynamics with agent interactions (Boerkamps et al., 2000; Hunt and Stefan, 2007; Wisetjindawat et al., 2007; Wang and Holguín-Veras, 2008; Samimi et al., 2012). Some of these applications are still based on passenger modelling using, for instance, a four-step approach (e.g. Wisetjindawat et al., 2007).

One of the potential advantages of including market dynamics in freight simulation is to evaluate the impact of changes in the form of agent interactions. For instance, on-line freight quotes or auctions have become common in many freight markets. These services facilitate the interaction between shippers and carriers in the market. This transaction form is expected to
result in a different vehicle flow configuration in a freight market since there are more opportunities to match supply (carrier services) with demand (commodity flows).

Therefore, the framework proposed in this dissertation has the objective to include market dynamics in freight modelling. It is expected that the three relevant components are represented in this framework. To accomplish all these objectives, the conceptual framework presented by Roorda et al. (2010) was selected as a starting point for three reasons.

First, commodity market, freight markets and transport operations are represented separately with the possibility of integrating them. Second, market dynamics can be represented through celebration of different forms of contracts (commodity and logistics services) between agents in both markets (commodity and freight). Finally, this framework assumes that agents have rational behaviour in the markets and operations decisions (transport operations) that is based on utility/profit maximization (rational behaviour).

Using all these elements, an agent-based freight simulation framework is proposed. FREMIS is presented briefly in this chapter and in more detail in Chapter 3. In FREMIS, the interactions in the freight market are represented by the Logistics Services Contract Formation stage, using the same terminology in Roorda et al. (2010). Two types of agents interact in this market: shippers (demand side) and carriers (supply side).

Shippers receive a list of shipments, an output of the commodity market (commodity contract formation in Roorda et al., 2010), and contract those shipments to logistics service providers in the freight market. Shippers perform two decisions. First, shippers bundle these shipments in contracts using a rational model (profit/utility maximization model). This model is motivated by the existence of economies of scope/scale in freight markets (e.g. backhaul shipments): shippers may obtain a lower rate by bundling similar shipments in contracts (see Sheffi, 2004 for a discussion about freight contracts and economies of scope). Second, shippers select a carrier for each contract using also a rational model, profit/utility maximization, based on carrier rates and levels of service. It is proposed that these two models are to be updated by learning/updating algorithms using information from the commodity market.
Carriers define their proposed rate (in $/km or $/km×ton) in each contract based on their level of service, their resources, their operational costs, and the competition in the market. For that, carriers consider their current and their future delivery network if the logistics services contract is included. With this formulation, product differentiation (carrier selection and carrier proposal models) and economies of scope/scale (shipment bundling and carrier proposal models) influence each carrier’s proposal. A similar approach was proposed by Liedtke (2009), which only incorporated economies of scope/scale in the formulation.

The outputs of the logistics service contract formation stage are logistics services contracts. Freight rates on these contracts are used to update carrier proposals with a learning/updating algorithm. Meanwhile, the characteristics of the shipments in all contracts of a carrier are used in logistics decisions to define modes, vehicle routes and consolidations (Roorda et al., 2010). The outputs of transport operations are observed carrier level of service and carrier costs. Carrier’s perceived level of service in the freight market is influenced by their observed level of service in contracts. A learning/updating algorithm represents this process. This information is used in market transactions by shippers. Carrier’s cost values used in the carrier proposal model are also updated by a learning/updating algorithm.

The complete implementation of this framework requires the estimation of models representing shipper decisions in the market. Agent interactions data (e.g. contracts, rates) are required to estimate these models. This is another critical obstacle in implementing a simulation of freight agent interactions. Even though these models are simplified, since they only represent agents disaggregate behaviour without considering directly interactions in the market (e.g. competition, strategic behaviour), these data are usually not available because they may represent strategic information for shippers and carriers.

Therefore, the available options are to implement surveys to collect revealed preference (RP), stated preference (SP) data or both. The definition of which type of data have to be collected depends on the freight market application. In this dissertation, a data collection procedure is implemented to permit the complete application of FREMIS, (see Chapter 4) for the GTHA freight market.
1.4. Thesis Outline

In the next chapter, a literature review of freight modelling is presented. The review starts with an analysis of comprehensive freight modelling frameworks used to forecast freight demand. The focus is on frameworks developed using passenger-based approaches. Next, an aggregate tour based modelling framework (Wang and Holguín-Veras, 2009) is analysed in more detail. This framework converts commodity flows into freight flows with a touring model. Consequently, it incorporates economies of scope and can be considered an aggregate alternative for FREMIS in urban freight markets. Then, disaggregate modelling approaches regularly adopted in freight studies are discussed. Such approaches have the advantage of minimizing aggregation bias and provide more behavioural realism in freight modelling. The final part of this chapter presents a review of freight microsimulation modelling frameworks, which represent agents’ interactions. These microsimulation frameworks combine disaggregate models with comprehensive frameworks to develop freight demand models.

In Chapter 3, the FREMIS formulation is presented with a special focus on its mathematical models. Each side of the freight market simulation is presented, including demand (see Section 3.2.1), supply (see Section 3.2.2), and how agents learn from their interactions. The framework is developed using the assumption that agents behave rationally (maximize profit/utility) in the market. The final part of Chapter 3 presents a discussion about the applicability of the framework, with the required information for its implementation, and some remarks related to calibration and validation of the framework.

Chapter 4 provides a description of the GTHA freight market. First, a description of the GTHA and its freight market is presented using information from Census Canada, the InfoCanada company database and some recent studies sponsored by Metrolinx. Next, the data collection procedure implemented for this research to collect information required for FREMIS implementation is explained. This section contains a short review on methods to collect respondents’ preference (stated and revealed) with a discussion on the calibration of models developed from stated preference data. Then, details of the survey design (sampling, questions, flow-chart, implementation) are presented. The last section presents some initial results from the survey: response analysis, distribution of carrier attributes, and a freight rate model.
Chapter 5 presents the first demand model required to implement FREMIS, a shipment bundling model (see Section 3.2.1). This model has the objective to represent shipper behaviour when they decide which shipments have to be combined in contracts to reduce freight rates. The proposed specification consists of an ordered logit model with a vehicle routing algorithm (e.g. Clarke-Wright). Only the results of the ordered logit model estimated using survey data are presented. The full implementation of this model requires a complete list of shipments from a commodity market, which was not available during this research.

Chapter 6 presents the results of the second demand model required for FREMIS implementation, a carrier selection model (see Section 3.2.1). This model is developed using data from a SP survey customized for each respondent (shippers). The proposed specification consists of a multinomial logit model with an assumption of heteroskedasticity (different variances / scales) among respondents. A function was estimated to represent the value of the scale parameter given the size of the shipper (sales volume). Three models were developed to analyse the nonresponse bias and the non-attendance problem in the SP survey.

The last chapter presents the conclusions and discussion of the results of this research project. It also presents future directions of this research agenda, which consist of implementing FREMIS framework to study freight markets.
Chapter 2

Literature Review

This dissertation focuses on the development of a comprehensive framework to simulate accurately freight markets. The simulation of freight markets is expected to provide better models for freight demand since freight transport is an output of freight market interactions (see Section 2.5). Current freight models do not incorporate agent (shippers and carriers) interactions. As a consequence, the impacts of these interactions in freight flows are not considered (Cambridge Systematics, 2007). This is caused by the extensive adoption of passenger-based approaches in freight modelling (Cambridge Systematics, 2007). When applied to freight modelling, they can be divided into two classes of methods (Ogden, 1992): factoring methods and UTMS-based (3 and 4-stages) methods. A literature review of these methods is presented and discussed in the first part of this chapter.

The second part of this chapter presents one identified aggregate formulation for tour formation modelling. One of its capabilities is the conversion of commodity flows into vehicle flows with a representation of economies of scope. This framework was developed by Wang and Holguín-Veras (2009) and it uses an entropy-based approach. This approach forecasts the most likely quantity of vehicle trips by tours in a region using commodity flows, a network of tours, and impedance of vehicle trips. In this section, their formulation is analysed in detail, and its limitations are discussed.

Traditional freight modelling frameworks use aggregate models. Disaggregate freight models result in higher accuracy since they minimize aggregation bias and are more sensitive to different policies if behavioural formulations are used (Winston, 1983). There is a considerable
literature on these models especially for intercity regions (Regan and Garrido, 2001; Chow et al., 2010). Most of these models are applied to forecast freight mode choice (e.g. binomial models: rail or road). The third part of this chapter consists of a short literature review of these models, mainly based on Regan and Garrido (2001) and Chow et al. (2010).

The application of freight modelling frameworks using disaggregate freight models will require microsimulation methods (Law, 2007). More recently, these frameworks have been developed and implemented for different geographic scopes: (1) urban models: Boerkamps et al. (2000), Wisetjindawat et al. (2007), Hunt and Stefan (2007), and Schroeder et al. (2012); (2) intercity/international models: de Jong and Ben-Akiva (2007), Liedtke (2009), Baindur and Viegas (2011), and Samimi et al. (2012). Besides these applications, other frameworks have been formulated recently but they are still mostly conceptual (e.g. Roorda et al., 2010).

Most of these applications do not have a representation of agent interactions in their formulation. As a consequence, they are not considered agent-based models by some (e.g. Bankes, 2002 and Tesfatsion, 2003). The presentation of a literature review of microsimulated freight modelling frameworks is the objective of the fourth part of this chapter. These frameworks are divided between frameworks with and without a representation of agents’ interactions (relevant for this dissertation). The focus of this review is on the formulation adopted by them for the problem of converting commodity flows into vehicle flows, i.e., freight market representation.

The last part of this chapter discusses the potential impact of market agent interactions in freight modelling. This discussion is elaborated based on the assumption that agents behave rationally. The main idea of this discussion is to establish the relationship between agent interactions, characteristics of freight systems (e.g. costs, facilities) and freight flows (output of the market). If this relationship exists, then changes in the freight system (e.g. new terminals, new highways) would simultaneously impact agent interactions and freight flows. As a consequence, the impacts of these changes would be complex to predict in freight markets. Another consequence of this relationship is that current freight modelling methods may provide inaccurate results since these methods do not have a representation for agent interactions.
2.1. Passenger-Based Freight Modelling Frameworks

Freight passenger-based modelling approaches can be classified into two methods (Chow et al., 2010): factoring and UTMS-based (3 or 4-stages) methods. Factoring methods involve forecasting future freight demand using factors that represent freight growth rates. The procedure consists of multiplying freight data (e.g. traffic, OD matrices, and economic variables in freight models) by growth factors to predict freight demand (Cambridge Systematics, 2007; Chow et al., 2010). Growth factor methods are usually implemented by government agencies and they are based on the assumption that the growth rate of freight flows is the same for all roads and this rate can be estimated using historical freight trends (linear or compound growth) or economic projections (factors per economic sector) (Cambridge Systematics, 2007; Chow et al., 2010). As a consequence, these methods are not able to represent localized/spatial changes (e.g. roads, facilities, land use) or market changes (e.g. technology).

Most of the applications in freight-related projects use a UTMS-based approach to model freight movements (National Cooperative Highway Research Program, 2008). These models are classified into two approaches (Ogden, 1992; Cambridge Systematics, 2007). Truck-based models have 3-steps, without modal split step, where the units of transport are trucks or vehicles. The steps are:

i) Trip generation: trip rates or regression models based on economic activity (e.g. employment)

ii) Trip distribution: gravity models or Fratar method

iii) Trip assignment: user equilibrium in a truck network, incorporating truck route restrictions

The other approach, commodity-based modelling, uses a 4-step approach where the unit of transport is weight (see Figure 2.3). These models may provide more accurate results than truck-based approaches since they incorporate the dynamics of the urban/regional economy by representing commodity movements (Holguín-Veras and Thorson, 2000; Regan and Garrido, 2001). Initial steps are similar in both approaches (generation and distribution). They also use similar types of models in these steps, regression and gravity models. The next step in the commodity-based approach is called vehicle loading model (Ogden, 1992) which is traditionally an application of payload factors (average weight of the cargo carrier by a vehicle) on the total
tonnage flow between zones by type of commodity (Cambridge Systematics, 2007). The vehicle loading model is particularly relevant for this research since FREMIS is an alternative approach to this model (see Chapter 3).

Figure 2.3: Commodity Based Models - Sequential Estimation

2.2. Tour-Based Entropy Aggregate Model

Wang and Holguín-Veras (2009) describe two entropy maximization formulations to estimate the tour flows of commercial vehicles. These formulations use first and second order conditions resulting in expressions for the estimation of tour flows.

Their formulation starts with the definition of three concepts:
- tour: sequence of nodes visited by a vehicle
- trip: individual vehicle movement connecting two consecutive stops in a tour
• tour flow: vehicle trips following a specific tour during a certain time period

The impedance incorporated in the model is composed of two components. The tour travel impedance is a summation of travel impedance in each trip while the tour handling impedance is a summation of handling impedance at each stop. Two formulations were presented in the paper, one with overall impedance of tours (sum of tour travel and tour handling impedances), and another with the two impedances separated. First-order conditions of the entropy maximization problem are formulated to provide expressions to estimate the number of tour flows in each tour.

This model estimates the most likely tour flows given a network of tours. A network of tours is composed of all tours that are occurring in an area. In Wang and Holguín-Veras (2009), a case study was presented where the network of tours was identified using data from a commercial vehicle travel diary survey. A total of 613 different tours representing 65,385 vehicle trips defined the network of tours in the case study. Another option proposed by Wang and Holguín-Veras (2009) is to develop a tour choice model which outputs the network of tours. This is the main shortcoming of this model since the identification of the complete network of tours in a region is a challenging task.

2.3. Disaggregate Freight Models

Disaggregate freight models are classified by Regan and Garrido (2001) in two classes: “behavioural” and “inventory” models. These terms exist only for classification purposes since some “inventory” models also have behavioural foundations (Regan and Garrido, 2001). The main distinctions between these model classes are the decision makers and their consequent decisions. Behavioural models focus on mode choice decisions made by shippers, while inventory models forecast freight transport demand (commodity and vehicle flows) from the viewpoint of an inventory manager (Regan and Garrido, 2001).

In Regan and Garrido (2001), behavioural models generally use a random utility maximization approach. The variables included in the utility formulation are components of the level of service offered by different freight services (e.g. fare, travel time, reliability). These models are usually applied to forecast mode choice decisions in intercity freight markets (Regan and
Garrido, 2001). Some recent approaches have been used to forecast vehicle-type choice decisions (e.g. Cavalcante and Roorda, 2009) which are more relevant in urban freight markets. Even though freight mode/vehicle-type choice models are different from passenger mode choice models, both usually use traditional discrete choices models with very similar specifications (Ortúzar and Willumsen, 2011), e.g. multinomial logit model.

On the other hand, inventory models attempt to integrate mode choice with production decisions using a consistent theoretical framework. They were developed and applied initially during the 1970s and early 1980s (McFadden et al., 1985; Regan and Garrido, 2001). Tyworth (1991) provides a review of these models. These models incorporate level-of service attributes into an optimal inventory control framework using multilevel models for joint decisions (e.g. shipment size and mode choice), and many of them have discrete/continuous specifications. Discrete/continuous models may have selectivity bias (Greene, 2003) and Mannering and Hensher (1987) present three correction techniques: indirect methods (e.g. instrumental variables approach), direct methods (e.g. bias correction term and expected value) and full information maximum likelihood.

Similar discrete/continuous models have been developed to integrate mode choice (discrete) and shipment size (continuous) without a consistent theoretical framework (Mannering and Hensher, 1987; Abdelwahab and Sargious, 1992; Holguín-Veras, 2002; Cavalcante and Roorda, 2010). They are not considered inventory models following the definition adopted by Regan and Garrido (2001). Mannering and Hensher (1987) called them models with a reduced form while inventory models were called models with an economic consistent structure.

There are other instances of multilevel disaggregate freight models. For example, Jiang et al. (1999) used a nested logit framework to represent the type of carrier (private or for-hire) and mode choice decision using disaggregate revealed preference data for shippers in France in 1988. The framework adopted has partial degeneracy (Hunt, 2000) since mode choices are only available for "public" (for-hire) carriers.
2.4. Freight Microsimulation Modelling Frameworks

2.4.1. Frameworks without agents interactions

Recent freight modelling frameworks have used microsimulation approaches in their formulation. The first framework was developed by Boerkamps et al. (2000), the GoodTrip model. This framework identifies four interconnected markets: commodity, transport services, traffic services, and infrastructure markets. Actors can have three roles: shipper, transporter and receiver. Boerkamps et al. (2000) do not present details of their models (e.g. formulation, specification, predictive or normative models) or detailed information regarding the representation of agent interactions.

They applied their framework to simulate the supply chain of food retailers in the city of Groningen (Netherlands). Their approach has one stage that represents the conversion of commodity flows to vehicle flows. This stage is influenced by the type of origin and destination of the commodity flow. They assumed that origin activity type influences the choice of transport mode, vehicle capacity, maximum loading factor, and maximum number of stops per tour while destination activity influences minimal delivery frequency.

Wisetjindawat et al. (2007) present a freight microsimulation model for Tokyo Metropolitan Area, in which agents’ behaviour and their relationship in supply chains are incorporated. Their model has the same stages as the commodity-based model (see Figure 2.3) although agent decisions use disaggregate models and these decisions are aggregated using microsimulation. The conversion of commodity flows into freight flows (vehicle loading model) is divided into three stages. First, a regression model is used to estimate the delivery lot size and frequency. Second, a nested logit model of carrier choice and vehicle type choice is used. Then, customers of each shipper, who have the same delivery frequency, carrier and vehicle, have their shipments grouped in tours using a vehicle routing model with a logistical approach to minimize route travel time.

Hunt and Stefan (2007) present a microsimulation system for modelling urban commercial movements applied to the City of Calgary (Canada). Their model does not explicitly represent
commodities or shipments, but rather uses a discrete choice approach to form tours. The model includes the following steps: tour generation, vehicle and tour purpose, tour start, next stop purpose, next stop location and stop duration.

This model is initiated similarly to truck-based approaches with a tour generation model. Tour generation is an aggregate trip generation model. Next, a tour formation microsimulation model is implemented using statistical models. The variables in these models include land use types (e.g. type, employment, population), measures of accessibility (population and employment), type of companies (e.g. industrial, retail, wholesale), and tour characteristics (purpose, vehicle type, travel time, number of stops). The complete modelling framework has a high degree of parametrization (identified in the paper: 561 parameters in 41 models) which reduce its applicability since it may require new parameters after changes in the urban system (e.g. land use, transportation system). Another aspect that reduces its applicability is that many parameter estimates were not statistically significant.

One example of a national freight micro-simulated model is presented by de Jong and Ben-Akiva (2007). This model operates at the level of individual firm-to-firm (sender to receiver) relations and simulates the choice of shipment size and transport chain for all relations within the country, exports and imports. The total model consists of three parts. First, production-consumption matrices give the flows of goods between two zones and the matrices are disaggregated from zone-to-zone flows to the level of firm-to-firm flows. Second, these flows are input into the logistics module, which determines frequency/shipment size, number of legs in the transport chain, use of consolidation and distribution centres, and the mode used for each leg. The output of the logistics module is the OD vehicle flows, which are used in the third part, the assignment of vehicle flows to the networks. The paper focuses on the logistics module. A random utility discrete choice model is specified by using the total annual logistics costs as the observed component of utility plus a random cost component. Empty vehicles are considered in the model by assuming that empty trucks move in the opposite direction of loaded origin–destination flows.
Wang and Holguín-Veras (2008) present a hybrid micro-simulation modelling framework to construct commercial vehicle tours that satisfy a known commodity flow origin-destination (OD) matrix in an urban freight market. Wang and Holguín-Veras use synthetic data to illustrate the procedure of converting commodity flows into vehicle tours. Initially, carriers are selected using a probabilistic model based on fleet size. Then, the tour construction process is decomposed into two parts: destination choice and tour termination decisions. Each of these parts is modelled using logit models. Tours are built in a simulation environment using these two models with a constraint for the maximum number of destinations in a tour.

Samimi et al. (2012) presents and validates the results of the mode choice component of a large-scale behavioural microsimulation framework, named Freight Activity Microsimulation Estimator (FAME). FAME consists of five modules: firm-type generation, supplier selection, shipment size determining, mode choice and network analysis. The disaggregate mode choice model is developed using data from a nationwide establishment survey conducted in 2009 in the United States. The final model used a probit specification and could predict correctly 95% of the mode choices in the sample. In the same paper, validation of the model is performed using an implementation of FAME until the fourth module (mode choice). The results are very similar to the FAF (Freight Analysis Framework implemented by US Federal Highway Administration) data except for the following types of commodity: coal, gravel and cereal grains.

2.4.2. Frameworks with agents interactions

Three freight microsimulation frameworks with agent interactions representation are included in this section: Liedtke (2009), Baindur and Viegas (2011), and Roorda et al. (2010). These frameworks are discussed next with a focus on their freight market representation. The framework in Liedtke (2009) has a market interaction module where shippers transform flows of goods into individual shipments creating contracts and assign them to forwarders (carriers) in a market environment. The assignments of shipment contracts to carriers occur in the following way.

On the demand side, shippers create a list of carriers and assign a score to each carrier. The value of the score is a function of the number of contracts awarded to the carrier and the average
number of contracts awarded to carriers by the shipper. The score is used to rank carriers in the list and carriers invited to present bids for a contract are defined based on this rank and on the maximum number of bids allowed for the contract (defined randomly). Shippers receive bids for each contract and assign (award) it to the carrier with the lowest bid.

On the supply side, carriers are invited to present bids for a contract and then calculate two costs related to the addition of this contract: marginal and full cost. The rate at which a carrier is willing to accept a contract is computed using a normalized weighted mean (sum of weights = 1) composed of both costs. This formulation allows the representation of short-term (rate → marginal cost) and long-term (rate → full cost) cost-recovering strategies.

Liedtke (2009) is a relevant contribution with a representation of economies of scope/scale but it does not incorporate an important element in freight markets: product differentiation. Carrier selection is based only on rate (shipper selects the lowest bid) and carrier bid model is based only on cost recovering (marginal or full cost). Therefore, this model is not based on a profit maximization approach (unless the market is in perfect competition). Besides that, the carrier’s bid model does not include any representation of carrier strategic behaviour when facing market competition. Consequently, Liedtke’s framework is not capable of representing freight market dynamics.

Baindur and Viegas (2011) introduce an agent-based modelling approach (named ANYLOGIC) to simulate intercity freight markets (the commodity market is not included). Their paper presents an implementation of this approach for a freight market offering transport services between two trading regions. Carriers included are road haulage companies and a single maritime-based intermodal transport company (road and ship). Three layers were incorporated in ANYLOGIC:

i) Regulatory layer: environment where market rules and conditions are determined

ii) Physical layer: representation of physical entities in the market (e.g. vehicles, ports, handling equipment and loading units)

iii) Market layer: representation of the market where their agents (shippers and carriers) are cognitive, goal seeking and have independent decision making abilities
In the market layer, lot size, frequency of delivery, time windows and shipment size are stochastically generated constrained by the total annual transported volume data. Using this information, each shipper in the simulation generates unitized shipments between trading regions. Then, shippers assign each shipment to a carrier. This process is simulated using a nested logit model with partial degeneracy (Hunt, 2000) having two levels: mode choice (road or maritime) and service choice (if alternative road is selected, which road haulage company is selected). This model is based on carrier attributes: quoted rate, expected delivery time, expected delay and expected damage rates.

On the supply side, carrier rates are fixed for a certain time and their rates are based on current vehicles (truck or ship) occupancy rates (loading units in the shipments / number of vehicles). Rates charged are kept constant unless occupancy rate is above or below specific thresholds. In this case, rate charged is increased or decreased, respectively. Another feature of the supply side is a model of entry / exit of carriers in the market. This model is based on current rates charged by carriers and a base case rate.

The framework developed by Baindur and Viegas (2011) incorporates product differentiation with a nested logit model for carrier selection. However, it does not incorporate economies of scope/scale and, similarly to Liedtke (2009), does not include any representation of carrier strategic behaviour when facing market competition. Furthermore, carrier bid (called quoted rate in their paper) in contracts is maintained constant in many situations. Nevertheless, their rate model resembles a revenue management model with capacity control since it is based on fleet occupancy rate (Talluri and van Ryzin, 2004).

Both papers presented outputs of case studies. The outputs of the case study in Liedtke (2009) are the distribution of shipment sizes and of total distance travelled and they have a high variability. In Baindur and Viegas (2011), the outputs are the distribution of market shares and of service prices and they have a small variability. Even though these outputs are different, their diverse patterns are expected because of their distinctive formulation: bids in Liedtke (2009) are defined for each contract while in Baindur and Viegas (2011), they are kept constant during a certain time period.
The last freight simulation framework identified in the literature with agent interactions is proposed by Roorda et al. (2010). There are three stages in their framework: commodity market, shipper-carrier market, and transport operations (see Figure 2.4). Two stages simulate markets by the celebration of contracts. In the commodity market, a commodity contract identifies a vendor, a customer, a price and a list of shipments from vendor to customer. In the freight market, a logistics contract identifies an agent responsible for shipments, an agent (a carrier) that executes shipments, a price and a list of shipments to be transported. In the other stage (transport operations), logistics decisions are simulated to represent operational decisions of logistics service providers during the movement of shipments. These three parts can be associated with traditional freight modelling stages (see Figure 2.4): commodity generation, commodity distribution, mode split / vehicle loading, and network assignment. The framework proposed by Roorda et al. (2010) has not yet been implemented.

![Figure 2.4: Conceptual Framework Stages](image)

### 2.5. Freight Modelling and Agents Interactions

Traditional freight modelling frameworks represent the conversion of commodity flows into freight flows by either estimating truck trips directly (truck-based model) or using a vehicle loading model with payload factors (commodity-based model). Payload factors may not be able to represent with accuracy the assignment of commodity flows (shipments) into vehicle flows (routes). This assignment is a process within an economic market and the resulting vehicle flows are dependent on how market agents interact. For instance, consider a region with five zones and commodity flows between zones 1 – 2, 1 – 5 and 3 – 4 (see Figure 2.5). Applying the
payload factors approach combined with empty reverse trips\textsuperscript{1}, the resulting truck trip matrix (Truck Matrix 1) would present three two-way flows with \( n_1 \), \( n_2 \) and \( n_3 \) truck trips in each direction between zones 1–2, 3–4, 1–5, respectively (see the network of these trips in the top right of Figure 2.5). However, suppose that, in reality, one carrier located at zone D is selected by shippers to deliver all shipments using \( n_1 \) truck trips with \( n_1 > n_2 \) and \( n_3 \) (see the network of these trips in the bottom right of Figure 2.5). The resulting truck matrix (Truck Matrix 2) is different than Truck Matrix 1:

- Zone productions and attractions are different for almost all zones (except zone 2)
- The number of empty trips changes (from \( n_1 + n_2 + n_3 \) to \( 2n_1 \)) which might represent a reduction in the freight market (if \( n_1 < n_2 + n_3 \))
- The total number of truck trips and number of vehicles also changes (from \( 2n_1 + 2n_2 + 2n_3 \) to \( 7n_1 \) and from \( n_1 + n_2 + n_3 \) to \( n_1 \), respectively)

\textbf{Figure 2.5: Truck Matrices Examples}

\textsuperscript{1} Some modelling frameworks attempted to model reverse empty trips (Holguín-Veras and Thorson, 2003; Holguín-Veras, Thorson and Zorrilla, 2010).
The influence of freight agent interactions in freight flows can also be identified using game theory. For instance, using the formulations derived by Holguín-Veras (2000) and by Berry (1994), the price function for a profit-maximizer carrier \( k \) in a Cournot-Nash game (Fudenberg and Tirole, 1991) would be:

\[
p_k(x_k, y_k, X) = c'(x_k + y_k) + s_k \left( \frac{\partial s_k}{\partial p_k} \right)
\]

where, \( X \) is the total supply (number of trips) in the market, \( x_k \) is the number of carrier \( k \) loaded trips, \( y_k \) is the number of carrier \( k \) empty trips, \( s_k = x_k / X \) is the market share of carrier \( k \) and \( c'(\cdot) \) is the marginal cost of carrier \( k \).

In Equation (2.1), a carrier’s market share (a vehicle flow measure) depends on carrier’s price (an element of agent interaction) and vice-versa, unless the market is in perfect competition (\( |\partial s_k / \partial p_k| \to \infty \)). Therefore, Equation (2.1) demonstrates the existence of endogeneity between price and other elements in a freight market, cost functions and market shares (quantity). Market shares are the output of agent interactions. One of the potential consequences is that freight modelling has to represent agent interactions to improve their accuracy and applicability. This conclusion is only valid if the assumption of agents’ rational behaviour is consistent with actual behaviour in the market.

Besides agent interactions, a formulation for costs in freight transport is required in a freight modelling framework. Freight transport costs depend on the characteristics of shipments delivered by a carrier, locations (origin and destination) and shipment size (weight/volume), and also on carrier characteristics: fleet (e.g. type of vehicles), facilities (e.g. intermodal terminals, distribution centres) and level of service. This relationship has been studied in operations research and supply chain literature using a different type of formulation, e.g. vehicle routing (Toth and Vigo, 2001) and logistics network (Simchi-Levi et al., 2003). One important consequence of this relationship is that vehicle flows due to a new shipment in the market depend on the current carrier assignment of shipments in the market (\( x_k \)). Therefore, some
carriers gain economies of scope or scale from being selected by a shipper (Tirole, 1988), which result in a competitive advantage.

Market shares can be predicted using the formulation presented by Ben-Akiva and Lerman (1985). Suppose that for a set of shipments (a contract) \( t \) the probability that a shipper \( s \) selects a carrier \( k \) to deliver shipments in this contract is \( P_{sk}(t) \). Then, for \( T \) contracts, the market share of carrier \( k \), based on total trips, is:

\[
S_k = \frac{\sum_{t=1}^{T} P_{sk}(t)x_{kt}}{\sum_{t=1}^{T} \sum_{j=1}^{K} P_{sj}(t)x_{jt}}
\]

where, \( x_{kt} \) and \( x_{jt} \) are the number of trips of carriers \( k \) and \( j \) in contract \( t \) and \( K_t \) is the total number of carriers competing for contract \( t \).

The value of \( P_{sk}(t) \) is a function of carrier’s attributes: level of service (e.g. time reliability) and price. This result has been validated by several freight mode choice studies (e.g. Winston, 1983; McFadden and Winston, 1985; Fowkes, 2007; Meixell and Norbis, 2008; Patterson et al., 2010) and therefore we can conclude that product (service) differentiation is an inherent characteristic of freight markets and therefore is required in any freight modelling framework.

As a conclusion, three elements would improve the ability of a freight modelling framework to accurately represent market behaviour: agent interactions, economies of scale/scope and product differentiation. These elements are formulated in a new freight modelling framework that is first presented in this thesis: FREight Market Interaction Simulation (FREMIS) Framework.
Chapter 3

Freight Market Interactions Simulation

This chapter presents the FREMIS formulation. First, the rationale for the adoption of an agent-based approach is provided. The rationale starts with an analysis of the aggregation problem in economics with a discussion of its commonly implemented approaches (Stoker, 1993). The focus then shifts to formulation of FREMIS for each side of the market: demand (shippers) and supply (carriers). Both sides are represented under the assumption that agents are rational. FREMIS incorporates elements of product differentiation and economies of scope/scale with information of the market under study (cost parameters and demand models). On the demand side, this approach results in two demand models: shipment bundling model and carrier selection model. The former model represents the process of shipment contract formation, based on cost advantages that shippers regularly obtain in the freight market (e.g. backhaul shipments). The latter model represents the carrier selection process, based on carriers’ attributes therefore embodying product differentiation in FREMIS simulation.

The supply side is formulated to specifically represent carrier short-run decisions (price strategies) in the market. Medium and long-run decisions, such as increase in carriers’ facilities (e.g. number of vehicles, distribution centres), and changes in local transportation infrastructure (e.g. new highways, intermodal terminals) are considered to be exogenous. The proposed formulation uses profit functions based on cost parameters, carriers’ resources, and information related to interactions in the market (chance of a carrier winning a contract given their bid on the contract).
The last part of this chapter discusses the data requirements for operationalization of FREMIS for case studies. Some requirements are the same as for traditional transportation modelling, such as characteristics of transportation network in the region of study. However, other specific information is also required such as cost parameters, shipper behaviour models, carriers’ level of service and characteristics of shippers and carriers.

3.1. The Rationale for an Agent-Based Approach

The main objective of FREMIS is to model the behaviour of a complete freight market. The problem of modelling aggregate market behaviour is well established in economic theory and it has been an important focus of research in macroeconomic theory literature (Ehrentreich, 2008). This literature is extensive and it mainly focuses on the discussion of how to represent the aggregate (macro) based on the disaggregate behaviour (micro). This approach is considered consistent but it is complex to fully implement (Stoker, 1993). There are three major approaches to empirically model aggregate market behaviour (Stoker, 1993; Ehrentreich, 2008):

- Modelling using only aggregate data, including the representative agent approach.
- Modelling individual economic behaviour alone, or microsimulation.
- Joint modelling of individual and aggregate level data.

There are two approaches to model using only aggregate data. The first one is to use regression models relating the output (e.g. vehicle flows) with the inputs of the market (e.g. commodity flows, freight rates) (Ehrentreich, 2008). These models were usually adopted before the 1980s in freight modelling (see the review by Regan and Garrido (2001)), and they were common in Macroeconomics until the mid 1970s when the Lucas’ critique was published (Lucas Jr., 1976). Lucas’ critique indicated the main shortcomings of macro analysis without micro foundations: inability to forecast policies that change the composition of the market (e.g. income distribution, company size, and company cost distribution) and the consequent inability to forecast long-run impact of policies. The former is crucial in the evaluation of economic related policies (e.g. tax incentives, transportation policies that reduce operational costs), which are expected to have an impact on the composition of the market.
Representative agent models are formulated based on representative consumer(s) and representative supplier(s). Since the 1990s this approach has been criticized by various authors (e.g. Kirman, 1992; Hartley, 1997) because it can only be applied satisfactorily under very restrictive sets of assumptions. According to Kirman (1992 p. 120): “these assumptions are so special that few economists would consider them plausible”. The main assumption necessary to permit the application of this approach is agent homogeneity. This assumption has been contested empirically since, according to Stoker (1993 p. 1827), “there are no studies or disaggregate, micro level data that fail to find strong systematic evidence of individual differences in economic behaviour”. Even though various critiques exist against this approach in the economic literature, some recent freight models were developed based on it (e.g. Rich et al., 2009).

The restrictions of aggregate frameworks and recent computational developments encouraged the formulation of micro-macro approaches (Ehrentreich, 2008). These approaches use a model representing the behaviour of each agent in the market (Stoker, 1993) and their interactions. Aggregation is performed using two frameworks:

- **Analytical frameworks (“top-down”)**: agent interactions are formulated analytically and aggregate market behaviour depends on equilibrium formulations (Nash equilibrium).
- **Agent-based/simulated frameworks (“bottom-up”)**: agents interactions are microsimulated in a computing environment that can be customized for different market structures and equilibrium points are identified from the analysis of simulation outputs.

The main distinction between these approaches is that simplifying assumptions are necessary in analytical approaches and not required in agent-based approaches. Tesfatsion (2006) concluded that for markets known to have a globally stable equilibrium these simplifications might be considered reasonable. This is probably not the case for freight markets, especially urban freight (Friesz and Holguín-Veras, 2005). Therefore, agent-based approaches would be more appropriate to model markets, where equilibrium assumptions do not hold. Based on this and the fact that many markets do not present perfect competition conditions, Bankes (2002) argues that the most fundamental reason for the enthusiasm with these approaches is not computational
development but the dissatisfaction with simplifying assumptions (restrictive or unrealistic) imposed by analytical modelling alternatives.

Bankes (2002) presented other advantages of agent-based approaches:

i) Agents are a natural ontology or representation formalism for many social problems: agent representation provides a place to concentrate a large amount of data and knowledge of a complex system

ii) The power to demonstrate emergent phenomena, which can be characterized as an accurate representation of macroscopic behaviour using a simulation of microscopic behaviour

Hence, according to Ehrentreich (2008), many researchers consider agent-based approaches as the latest revolution in economic methodology. To accurately model complex economic markets, agent-based models treat the economy as an evolving complex adaptive system, consisting of many heterogeneous and interacting agents (Ehrentreich, 2008). Agent-based models permit the incorporation of many challenging issues in aggregate market modelling such as (Tesfatsion, 2006): asymmetric information, strategic interaction, expectation formation on the basis of limited information, mutual learning, social norms, transaction costs, externalities, market power, predation, collusion, and the possibility of coordination failure. These issues can be incorporated in many different ways and a simulation framework using agent-based models will favour an immersed analysis of market structures.

Since freight markets present characteristics that violate perfect competition conditions (Tirole, 1988) (e.g. product differentiation and economies of scale/scope), agent-based modelling is probably the most appropriate approach to simulate freight markets’ aggregate behaviour. In the case of urban freight markets, agent-based models may be the only approach recommended for these markets, because these markets are seldom, if ever in any kind of stationary equilibrium (Friesz and Holguín-Veras, 2005).

However, there are still some issues with Agent-Based Modelling (ABM). Bonabeau (2002) identify two main shortcomings of this modelling framework. First, the task associated with accurately modelling the individual behaviour of human agents is challenging because of potentially irrational behaviour, subjective choices and complex psychology. Second, the high
computational requirements to implement this type of framework since ABM attempts to simulate the behaviour of individual agents and their interactions with other agents. To mitigate these shortcomings, FREMIS is formulated using simplified behavioural models and the traditional assumption of rational behaviour of economic agents.

### 3.2. FREMIS Formulation

FREMIS is formulated using the conceptual framework presented by Roorda et al. (2010) as the general framework because (see Figure 3.1):

- Commodities markets, freight markets and transport operations are represented separately with the possibility of integrating them
- Market interactions can be represented through the celebration of different forms of contracts (commodity and logistics services) between agents in both markets (commodity and freight markets)
- The conceptual framework assumes that agents have rational behaviour in the markets (commodity and freight) and in operating decisions (transport operations) based on utility/profit maximization and it permits the incorporation of product differentiation and economies of scope/scale
The freight market is represented in Roorda et al. (2010) in the following way. Carriers (logistics firm in their paper) advertize their price values in a certain period as a function of the characteristics of a set of shipments: weight, type of commodity, location of the shipments (origin and destination). The price function is also a function of the resources available to carriers (costs). Shippers bundle shipments in contracts based on locations (e.g. similar transportation corridor), type of commodity (e.g. with similar handling characteristics) and similar service requirement (e.g. speed and reliability). Shippers (business establishments in their paper) collect information about price and form a choice set of suitable carriers for each contract. Shippers select a carrier using a random utility model based on carriers’ attributes and prices. None of the models proposed in Roorda et al. (2010) have a detailed specification (e.g. functional form) or are estimated by them.
FREMIS is developed based on this conceptual framework incorporating many other aspects such as: a probabilistic formulation for the decision of bundling shipments in a contract, a learning approach for shippers (to acquire information about level of service) and carriers (to acquire information about the competition), carrier pricing models for each contract based on the locations (incorporating economies of scope) and competition in the market (incorporating product differentiation). The framework is also flexible and it can incorporate some other aspects such as different carrier pricing strategies (cost-plus pricing, different risk attitudes), inclusion of 3PL companies, and different representation for transactions in freight markets.

Using the same terminology as Roorda et al. (2010), the interactions in FREMIS are represented by the Logistics Services Contract Formation stage. Two types of agents interact in this market: shippers (demand side) and carriers (supply side). It is assumed that agents exhibit rational behaviour. Therefore their main objective in the market is to maximize their individual profit/utility values. The FREMIS flow chart is presented in Figure 3.2 and its elements are discussed in the next sections. The first version of this framework was presented at 2012 IATBR conference (Cavalcante and Roorda, 2012).
Figure 3.2: FREMIS Framework
3.2.1. FREMIS: Demand Side

Shippers receive a list of shipments from the Commodities Market (Commodity Contract Formation in Roorda et al., 2010) to contract logistics services in the freight market. Shippers perform two sequential decisions to maximize their utility level (resulting from the interactions between producers and receivers in the commodity market):

- Selection of the shipments in each contract: Shipment Bundling Model.
- Carrier selection for each contract: Carrier Selection Model.

Since economies of scale/scope are present in freight markets, shippers have an incentive to combine diverse shipments in the same contract because it may result in reduced contract costs. Based on Song and Regan (2003), contracts (called lanes in their paper) are created as a function of the relationship between market expected price of delivering a bundle with $n$ shipments $p(s_1 \cap s_2 \cap \ldots \cap s_n)$ and the sum of market expected prices of delivering the same $n$ shipments individually $p(s_1) + p(s_2) + \ldots + p(s_n)$. Using this relationship, a set of shipments is classified by Song and Regan (2003) in three ways:

- **Complementary**: $p(s_1 \cap s_2 \cap \ldots \cap s_n) < p(s_1) + p(s_2) + \ldots + p(s_n) \rightarrow$ combine shipments
- **Substitute**: $p(s_1 \cap s_2 \cap \ldots \cap s_n) > p(s_1) + p(s_2) + \ldots + p(s_n) \rightarrow$ do not combine shipments
- **Additive**: $p(s_1 \cap s_2 \cap \ldots \cap s_n) = p(s_1) + p(s_2) + \ldots + p(s_n) \rightarrow$ indifferent

There are some types of shipments that have to be combined regularly, such as backhaul truckloads. Backhaul is the return movement of a truck from a destination to the point of origin. A backhaul truckload occurs when both movements (backhaul and original haul, named head haul) have loads. For these shipments, the market expected price of the combined contract would often be lower than individual contracts, because the same vehicle can be used in both shipments. In all other situations, the decision depends on the characteristics of the freight market since the market expected price is defined endogenously (see Equation (2.1) for a Cournot-Nash equilibrium). Therefore, this model requires a development based on agents’ perceptions of the characteristics of the freight market and, ideally, using a probabilistic shipment bundling model developed from revealed or stated preference data.
In the case of urban freight, the proposition is a probabilistic model that relates the concept of dead head distances (distance travelled by freight vehicles without cargo) and distances to locations with large concentration of freight flows (e.g. downtown areas, seaports, airports). For instance, if the savings of a combination $U$ of $S$ shipments is $DHD_{SU}$ and $d_{1U}, d_{2U}, \ldots, d_{PU}$ the distances between shipment’s origin/destination and $P$ freight poles (locations with a concentration of freight flows) in a region, then the probability that these $S$ shipments would be bundled is:

$$
P_B(U) = \frac{e^{\mu_b \left( \beta_{SAV} DHD_{SU} + \sum \beta_{d_p} d_{pu} \right)}}{e^{\mu_b \left( \beta_{SAV} DHD_{SU} + \sum \beta_{d_p} d_{pu} \right)} + \sum_{W \neq U} e^{\mu_b \left( \beta_{SAV} DHD_{pu} + \sum \beta_{d_p} d_{pw} \right)}}
$$

(3.1)

where:

- $\beta_{SAV}$ and $\beta_{d_p}$: parameters to be estimated from revealed or stated preference data;
- $\mu_b$: scale parameter of the Gumbel distribution which can be obtained in the calibration process since it is usually set to one to permit the identification of $\beta_{SAV}$ and $\beta_{d_p}$.

After shipments are bundled, shippers enter the freight market to select a carrier that would maximize their profit/utility by providing logistics services for each bundle of shipments. Since shippers’ profit/utility in freight markets is a function of carrier’s attributes (level of service), carrier’s performance in the market (reputation and past experience) and price (Winston, 1983; McFadden and Winston, 1985; Fowkes, 2007; Meixell and Norbis, 2008; Patterson et al., 2010), shippers have to obtain information about carriers’ level of service. With this information, shipper $s$ selects a carrier $k$ among $K_t$ carriers for each contract $t$ based on the following linear utility function using a multinomial logit model:
\[ V_{sk}(t) = \beta_{LS}LS_{kl} + \beta_{R}R_{sk} + \beta_{E}E_{sk} + \beta_{p}P_{sk} \]  
(3.2)

\[ P_{sk}(t) = \frac{e^{\mu V_{sk}(t)}}{e^{\mu V_{sk}(t)} + \sum_{j \neq k} e^{\mu V_{sj}(t)}} \]  
(3.3)

\[ LS_{kl} = \sum_{l=1}^{L} \gamma_{l}X_{kl} \]  
(3.4)

where:

- \( LS_{kl} \): expected level of service of carrier \( k \) in contract \( t \)
- \( R_{sk} \): reputation (a rating) of carrier \( k \) in the freight market estimated by shipper \( s \)
- \( E_{sk} \): experience of shipper \( s \) with carrier \( k \) based on the performance on previous contracts
- \( P_{sk} \): price of carrier \( k \) in contract \( t \) of shipper \( s \)
- \( \mu_{s} \): scale parameter of Gumbel distribution assuming shippers heteroskedasticity which can be estimated in a calibration/validation process
- \( X_{kl} \): attribute of carrier \( k \) that influences its level of service
- \( \beta_{LS}, \beta_{R}, \beta_{E}, \gamma_{l} \) and \( \beta_{p} \): parameters to be estimated using revealed or stated preference data

Various elements of a real freight market are incorporated in Equations (3.2) to (3.4). First, shipper’s utility is based on the level of service provided by carrier \( k \). Some attributes in level of service formulation \( X_{kl} \) are related to features of the transportation system, e.g. time reliability.

Second, carrier reputation in the market \( R_{sk} \) represents the lower risk that a shipper has when it selects a carrier with a good reputation in the market. The last element is the experience that a shipper has with a specific carrier \( k \), \( E_{sk} \).

Carriers’ level of service is private information and carriers may use strategic behaviour while interacting in the market. For instance, carriers may advertise a high and unrealistic level of service to win some big contracts. While doing so, they know that the level of service provided will be lower than advertised, resulting in a low probability of being selected again. Therefore,
they may assume that the cost of losing future contracts from the same shipper would still result in an increase in their profit. The principal-agent problem is used to study such situations (Laffont and Martimort, 2002) and it is the main component in economic contract theory (Bolton and Dewatripoint, 2005). In this theory, there are two groups of models: hidden information (or adverse selection) and hidden actions (or moral hazard). The former is used to model the selection of an agent (carrier) when the principal (shipper) does not have complete information (e.g. carrier’s time reliability). The latter is used to model the behaviour of agent (carrier) after the contract between agent and principal (shipper) is celebrated. Examples of such behaviour are lack of commitment to a high level of reliability in a celebrated contract given that would not result in benefits for carriers. In FREMIS, these models are used as a theoretical basis in the formulation of agent learning models. Many different agent-learning models exist in economic and psychology literature (Brenner, 2006) that can be used in FREMIS. We propose a moving average approach for shippers to estimate the expected level of service of carrier $k$ in contract $t$, $LS_{k,t}$. This model is simple to implement and it represents shippers who update their carriers’ perceived level of service based on experiences in the market with carriers. Suppose that a shipper $s$ had $n$ contracts with carrier $k$. Therefore, the value of $LS_{kst}$ would equal the average level of service with carrier $k$ until contract $n$ with shipper $s$:

$$LS_{kst} = E[LS_{k,s,n}] = E[LS_{k,s,n-1}] + \left(\frac{1}{n}\right)\left[LS_{k,s,n} - E[LS_{k,s,n-1}]\right]$$  (3.5)

Equation (3.5) can be modified to represent the situation when a shipper acquires some information of carrier’s level of service in the market (screening process in contract theory literature) or when a carrier advertises its level of service to a shipper (signalling process in contract theory literature). This value $LS_{k,BEF}$, the level of service before the interaction in the market, would substitute the value of $E[LS_{k,s,n-1}]$ and the relevance of this information for each shipper $s$ and carrier $k$, $\alpha_{sk}$ ($0 < \alpha_{sk} < 1$), would substitute $1/n$. Therefore, the expected level of service of carrier $k$ for shipper $s$, $LS_{k,s,AFT}$, would be equal to:
\[ LS_{k,s,AFT} = LS_{k,BEF} + \alpha_{sk} \left( LS_{k,s,n} - LS_{k,BEF} \right) \]  

(3.6)

Equation (3.6) is the formulation of the Q-learning method (Waltman and Kaymak, 2008), a type of reinforcement learning, where \( \alpha_{sk} \) represents the learning rate, values close to zero represent small learning (new information is not important), values close to one represent high learning (new information is important), and \( LS_{k,s,n} \) represents the new information. This type of learning method is apparently most suitable for updating carrier level of service given shipper’s experience in each contract because it is based on a simple average formulation, see Equation (3.5). Nevertheless, more research is needed in terms of the application of this framework and calibration of the parameters using secondary data from a region (e.g. commodities survey, traffic counts). Equation (3.6) can be used to formulate the Learning Algorithm 3 proposed in Figure (3.2).

Expected level of service of carrier \( k \) for each shipper \( s \), \( LS_{k,s,AFT} \), is an important element in the estimation of the values of \( R_{sk} \) (carrier’s reputation in the market) and \( E_{sk} \) (experience of shipper \( s \) with carrier \( k \)). These variables are proposed to use a rating scale to simplify the estimation of models. A Likert scale from 1 – Very Poor to 7 – Exceptional is proposed since this type of scale is the regularly used in surveys (Dillman et al., 2009). A specific survey is required to develop a function relating \( R_{sk} \) and \( E_{sk} \) with the values of \( LS_{k,s,AFT} \).

One possible approach is to use a linear function between \( R_{sk} \), \( E_{sk} \) and values of \( LS_{k,s,AFT} \). First the value of the expected level of service of carrier \( k \) in the market in a given period of time, \( LS_k \), is defined in the following way:

\[
LS_k = \frac{\sum_{s} LS_{k,s,AFT}}{S} , \quad s = 1, \ldots, S 
\]  

(3.7)

From these values, the rate of \( R_{sk} \) and \( E_{sk} \) can be obtained using Equations (3.8) and (3.9). These equations are formulated assuming that the maximum level of service in the market is
equal to the maximum rate (equal to 7) and minimum level of service equal to the minimum rate (equal to 1) for reputation and experience.

\[
R_{sk} = 1 + 6 \frac{LS_k - \min(\mathbf{LS})}{\max(\mathbf{LS}) - \min(\mathbf{LS})}
\]

(3.8)

\[
E_{sk} = 1 + 6 \frac{LS_{k,,AFT} - \min(\mathbf{LS}_{AFT})}{\max(\mathbf{LS}_{AFT}) - \min(\mathbf{LS}_{AFT})}
\]

(3.9)

where, \( \mathbf{LS} \) is the vector of expected level of service of carriers in the market and \( \mathbf{LS}_{AFT} \) is the vector of expected level of service of carriers who had contracts with shipper \( s \).

### 3.2.2. FREMIS: Supply Side

Carriers have resources (vehicles and facilities) and they compete in the freight market by making three decisions: one in the short-run (i.e. price proposal in a contract) and two in the medium/long-run (i.e. level of service offered in the market and carrier resources). This section describes the supply side of FREMIS only for short-run carrier decisions, such as freight rate ($/km or $/km × ton) in contract proposals. Other decisions, such as investments in new facilities or vehicles, are considered exogenous. Since FREMIS assumes that carriers are rational, a profit/utility formulation for each carrier in each contract is required. Two formulations are required: one for carriers who do not have a contract and another for carriers with at least one contract. First, suppose that a carrier \( k \) does not have another contract and has \( N_k^w \) vehicles of type \( w \). For a contract \( t \), carrier \( k \) has to define a price proposal to compete for contract \( t \) based on the following expected profit formulation:

\[
\pi_{skt}^{NO} = p_{skt} P_{sk}(t) - \left[ \sum_{w=1}^{W} c_k^w d_{st}^w P_{sk}(t) \delta_{st}^w + \sum_{w=1}^{W} c_k^w N_k^w + F(LS_k) \right]
\]

(3.10)

\[
\text{Cost function}
\]

where:
- \( \pi_{skt}^{NO} \): estimation of profit of carrier \( k \) for contract \( t \) from shipper \( s \) if carrier \( k \) does not have another contract;
- \( P_{skt} \): price proposal of carrier \( k \) in contract \( t \) of shipper \( s \);
• $P_{sk}(t)$: probability of carrier k winning contract t of shipper s;
• $c^d_k$: variable cost per distance travelled for carrier k by type of vehicle w;
• $d^w$: distance travelled by type of vehicle w in contract t of shipper s;
• $\delta^w$: indicator variable to define if type of vehicle w is used ($\delta^w = 1$) or not ($\delta^w = 0$) in contract t of shipper s;
• $c^N_k$: fixed cost by period of time (e.g. month) for carrier k for each type of vehicle w;
• $N^w_k$: number of vehicles of type w owned/leased by carrier k;
• $F(LS_k)$: fixed cost by period of time (e.g. month) of carrier k to provide a level of service $LS_k$ in the market.

The average values of $c^d_k$ and $c^N_k$ can be obtained from the publications that report information about operating cost of freight services (e.g. Transport Canada, 2005) and a probability, such as the lognormal distribution which is recommended for economic positive variables (Greene, 2003), can be used to simulate different values for each carrier. The value of $\delta^w$ is defined in the contract proposal and it is related to the minimum number of vehicles necessary to provide delivery services for contract t. The value of $F(LS_k)$ is related to the two long-run decisions made by carrier k: level of service and carrier resources (facilities). More research is needed to obtain information about this function and it is considered constant in this paper. Therefore, carrier k uses Equation (3.10) to make two decisions: $p_{skt}$ (short-run) and $N^w_k$ (medium/long run).

Since number of vehicles $N^w_k$ is fixed for a certain period of time, carrier k has to use the following first-order condition on price in contract t for maximization of profit $\pi_{skt}^{NO}$:

$$\frac{\partial \pi_{skt}^{NO}}{\partial p_{skt}} = P_{sk}(t) + P_{skt} \frac{\partial P_{sk}(t)}{\partial p_{skt}} - \sum_{w=1}^{W} c^d_k d^w \frac{\partial P_{sk}(t)}{\partial p_{skt}} \delta^w = 0$$
\[ P_{skt} = \sum_{w=1}^{W} c_k^w d_{st}^w \delta_{st}^w - \frac{P_{sk} (t)}{\partial P_{sk} (t) / \partial P_{skt}} \]

(3.11)

Equation (3.11) is similar to Equation (2.1) with a cost component (the first term on the right side) and a component that represents the structure of the freight market (the second term on the right side). Therefore, carrier \( k \) has to obtain some information about the market to maximize its expected profit.

Secondly, suppose that carrier \( k \) does have a certain number of contracts, which generate a revenue level \( R_k \) and distance travelled \( d_k^w \) by type of vehicle in these contracts. There are two profits: a known profit before contract \( t \) and an expected profit after contract \( t \) (assuming that carrier \( k \) bids on this contract).

\[ \pi_k = R_k - \left[ \sum_{w=1}^{W} c_k^w d_{st}^w \delta_{st}^w + \sum_{w=1}^{W} c_k^w N_k^w + F(LS_k) \right] \]

(3.12)

\[ \pi_{\text{WITH}} = p_{skt} P_{sk} (t) - \left\{ p_{sk} (t) \sum_{w=1}^{W} c_k^w d_{st}^w \delta_{st}^w + \left[ 1 - P_{sk} (t) \right] \sum_{w=1}^{W} c_k^w d_{st}^w \delta_{st}^w \right\} + 
\]

\[ + R_k - \sum_{w=1}^{W} c_k^w N_k^w - F(LS_k) \]

\[ \pi'_{\text{WITH}} = p_{skt} P_{sk} (t) - \left\{ p_{sk} (t) \sum_{w=1}^{W} c_k^w d_{st}^w \delta_{st}^w + \left[ 1 - P_{sk} (t) \right] \sum_{w=1}^{W} c_k^w d_{st}^w \delta_{st}^w \right\} + 
\]

\[ + \pi_k + \sum_{w=1}^{W} c_k^w d_{st}^w \delta_{st}^w \]

\[ \pi''_{\text{WITH}} = p_{skt} (t) - P_{sk} (t) \left\{ \sum_{w=1}^{W} c_k^w d_{st}^w \delta_{st}^w - \sum_{w=1}^{W} c_k^w d_{st}^w \delta_{st}^w \right\} \]

(3.13)

where:

- \( \pi_k \): current profit of carrier \( k \) based on not expired contracts
\( \pi_{skt}^{WITH} \): estimation of profit of carrier \( k \) for contract \( t \) from shipper \( s \) if carrier \( k \) does have another contract

\( d_{st}^{w,WITH} \): is the distance travelled combining current carrier \( k \) contracts and contract \( t \) in a delivery network

\( \delta_{st}^{w,WITH} \): indicator variable to define if type of vehicle \( w \) is used (\( \delta_{st}^{w} = 1 \)) or not (\( \delta_{st}^{w} = 0 \)) in current carrier \( k \) contracts and contract \( t \) in a delivery network

The first-order condition on price in contract \( t \) for maximization of profit \( \pi_{skt}^{WITH} \):

\[
\frac{\partial \pi_{skt}^{WITH}}{\partial P_{skt}} = P_{skt}(t) + P_{skt} \frac{\partial P_{sk}(t)}{\partial P_{skt}} - \frac{\partial P_{sk}(t)}{\partial P_{skt}} \left[ \sum_{w=1}^{W} c_k d_{st}^{w,WITH} \epsilon_{st}^{w,WITH} \delta_{st}^{w,WITH} - \sum_{w=1}^{W} c_k d_{st}^{w,WITH} \delta_{st}^{w} \right] = 0
\]

\[
P_{skt} = \left[ \sum_{w=1}^{W} c_k d_{st}^{w,WITH} \epsilon_{st}^{w,WITH} \delta_{st}^{w,WITH} - \sum_{w=1}^{W} c_k d_{st}^{w,WITH} \delta_{st}^{w} \right] - \frac{P_{sk}(t)}{\partial P_{sk}(t) / \partial P_{skt}}
\]

Equations (3.11) and (3.14) permit the simulation of interactions/product differentiation in the freight market (probabilities/price term) and represents the effect of economies of scope/scale (cost term) on carrier’s pricing behaviour. The simulation of interactions/product differentiation depends on the estimation of the probability of winning a contract \( t \) for a carrier \( k \) which is a function of the carrier price for contract \( t \) and carrier’s attributes (see Equation (3.2)) and also how shippers and carriers perform their transactions (e.g. auctions, request for proposals).

On the other hand, the representation of economies of scope and economies of scale depends on the cost functions in Equations (3.10) and (3.12) and on the characteristics of shipments in the freight market. Since resources are fixed in the formulation presented in this thesis (e.g. number of vehicles are fixed), cost of a carrier \( k \) for each contract \( t \) is only a function of the distances travelled by all types of vehicles (\( d_{st}^{w,WITH} \) and \( d_{st}^{w} \)) to serve contract \( t \) and current set of contract \( C \) of carrier \( k \). These distances depend on the quantity of goods of shipments in the contracts and on other characteristics of these shipments, such as origins, destinations and type of commodity. These distances can be calculated using some type of vehicle routing algorithm such (e.g.
Clarke-Wright algorithm) to minimize total delivery costs ($\sum c_k^d w^s t^w \delta^w_t$ and $\sum c_k^d w^s t^w \delta^w_t$) and calculate the values of distance travelled ($d^w_{st}$ and $d^w_{st}$) and number of vehicles by type ($\delta^w_t$ and e).

In order to identify whether Equations (3.11) and (3.14) are representing economies of scale or economies of scope or both in a given situation, the concepts of output, scope and scale of a carrier should be introduced. A carrier, as well as other transportation companies, produces movements from many origins to many destinations during many different periods (Jara-Díaz, 2000). Therefore, the output of a carrier is a set of flows ($Y$). According to Jara-Díaz (2000) and Jara-Díaz and Basso (2003), scale analysis focuses on the behaviour of cost as flows in all markets served by a firm (carrier) expand proportionally. Meanwhile, scope analysis focuses on the cost advantages or disadvantages of one company serving a complete set of distinct flows in the market. Economies of scope are usually more relevant to transportation companies since transportation costs are influenced to a greater extent by economies of scope (Sheffi, 2004) and transport network expansion should be analyzed using the concept of economies of scope (Jara-Díaz and Basso, 2003).

In FREMIS, the carrier price function (Equations (3.11) and (3.14)) is representing economies of scale when a new contract is proportionally expanding the current flows (in the shipments) of the carrier. In this case, the distance travelled would remain constant if current flows are expanded up to the capacity of current vehicles in carrier’s fleet. The representation of economies of scope occurs when a new contract has flows with distinct locations than current flows of the carrier and the carrier has some cost advantage to serve this contract, called economies of spatial scope by Jara-Díaz (2000). The degree of economies of scale and of economies of scope can be estimated using Equations (3.15) and (3.16), respectively, which were proposed by Baumol, Panzar and Willig (1982).

$$S = \frac{C(Y)}{\sum_i Y_i \frac{\partial C(Y)}{\partial Y_i}} \quad (3.15)$$

$$SC_R = \frac{C(Y_R) + C(Y_{M-R}) - C(Y_M)}{C(Y_M)} \quad (3.16)$$
where:

- \( S \): degree of economies of scale for a multiproduct set \( Y \)
- \( Y \): vector of the output of a carrier in the market – set of flows
- \( C(Y) \): cost of carrier as function of the output in the market
- \( Y_i \): one element of \( Y \)
- \( SC_R \): degree of economies of scope at \( Y_M \) relative to the product set \( R \)
- \( Y_R \): subset of a set of flow \( Y_M \)

Using Equations (3.10), (3.11), (3.13) and (3.14), another relevant decision can be simulated: whether carrier \( k \) should bid in contract \( t \) or not. An initial approach can be to prevent carrier \( k \) from bidding in contract \( t \) if \( \pi_{skt}^{NO} < 0 \), negative profit, or \( \pi_{skt}^{WITH} - \pi_k < 0 \), negative increment in profit. Assuming that carrier \( k \) follows price policies in Equations (3.11) and (3.14) and knowing that \( \partial P_{sk}(t)/\partial p_{skt} \) is negative, the following conditions should hold for carrier \( k \) bids on contract \( t \) (formulation is simple and it is not presented):

- Carrier \( k \) does not have a contract:
  \[
  \frac{P_{sk}(t)^2}{|\partial P_{sk}(t)/\partial p_{skt}|} \geq \sum_{w=1}^{W} c_k^{N^w} N_k^w + F(LS_k)
  \]  
  \[ (3.17) \]
- Carrier \( k \) does have at least one contract:
  \[
  \frac{P_{sk}(t)^2}{|\partial P_{sk}(t)/\partial p_{skt}|} \geq 0
  \]  
  \[ (3.18) \]

The condition in Equation (3.18) always holds. This result is expected. If a carrier \( k \) can deliver the shipments in contract \( t \) without increasing the number of vehicles, then bidding in contract \( t \) will result in a positive result (or zero) for the expected value of the increment in profit, i.e. the expected benefit of bidding in such contract is always positive or equals to zero for carrier \( k \). Meanwhile, the condition presented in Equation (3.17) is valid for carriers that follow the approach of not bidding in a contract \( t \) if it will result in a negative profit (\( \pi_{skt}^{NO} < 0 \)). These results are only valid if carriers are assumed to have a strategy for maximizing profit in the short-term. However, since the current stage of FREMIS includes only short-run carrier decisions, these results can be used to represent the decision to bid or not on a contract \( t \).
In Equations (3.11), (3.14), (3.17) and (3.18), two important values have to be estimated for carrier \( k \) for each contract \( t \): \( P_{sk}(t) \) and \( \partial P_{sk}(t)/\partial p_{skt} \). Two methods can be used. First, a carrier \( k \) may be able to predict accurately these values using Equations (3.2) to (3.4). The value of \( P_{sk}(t) \) is provided in Equation (3.3) and the value of \( \partial P_{sk}(t)/\partial p_{skt} \) can be obtained using Equation (3.19) (Train, 2009). Consequently, Equations (3.11), (3.14), (3.17) and (3.18) can be substituted by Equations (3.20), (3.21), (3.22), respectively. This approach can be used if carriers are able to predict their probability of winning a contract and it does not include any learning process for carriers while interacting in the market.

\[
\frac{\partial P_{sk}(t)}{\partial p_{skt}} = \beta_p P_{sk}(t) [1 - P_{sk}(t)] \tag{3.19}
\]

\[
P_{sk} = \sum_{w=1}^{W} c_k^w d_{st}^w \frac{P_{sk}(t)}{\beta_p P_{sk}(t) [1 - P_{sk}(t)]} + \sum_{w=1}^{W} c_k^w d_{st}^w \delta_{st}^w + \frac{1}{\beta_p [1 - P_{sk}(t)]} \tag{3.20}
\]

\[
P_{sk} = \left[ \sum_{w=1}^{W} c_k^w d_{st}^w \delta_{st}^w \right] + \left[ \sum_{w=1}^{W} c_k^w d_{st}^w \delta_{st}^w \right] + \frac{1}{\beta_p [1 - P_{sk}(t)]} \tag{3.21}
\]

\[
\frac{P_{sk}(t)}{1 - P_{sk}(t)} \geq \beta_p \left[ \sum_{w=1}^{W} c_k^w N^w_k + F(LS_k) \right] \tag{3.22}
\]

A second approach is proposed to simulate the learning process that happens with each carrier \( k \) based on market interactions. This approach uses Q-learning and numerical differentiation. To estimate the value of \( P_{sk}(t) \), a Q-learning approach is proposed. First, a carrier \( k \) defines a price policy for a certain period of time using a freight rate in $/km, \( r_{k0} \). The freight rate is used instead of the contract price because the rate is more similar between different contracts which would simplify the process of establishing a price strategy for a carrier. This is an assumption for carrier behaviour in this framework. An initial value for this rate can be derived using only costs parameters: \( r_{k0} = c_k^w \) if vehicle type \( w \) is used in contract \( t \). In each contract that carrier \( t \) bids on, the result of the proposal using price policy zero (\( r_{k0} \)) is recorded: \( \lambda_{rk0} = 1 \) if carrier \( k \) wins contract \( t \) and \( \lambda_{rk0} = 0 \) otherwise. The initial estimate of \( P_{sk}(t) \) can be equal to \( 1 / \) number of carriers in freight markets with carriers of similar size or equal to the market share (carrier
After carriers participation in \( n_0 \) contracts using pricing policy \( r_{k0} \), the expected value of \( P_{sk} (t) \), \( P_k (t) \), would be (\( \eta_k \) is the learning rate):

\[
P_{k,0,AFT} (r_{k0}) = P_{k,0,BEF} (r_{k0}) + \eta_k \{ \lambda_{r_{k0}} - P_{k,0,BEF} (r_{k0}) \} \tag{3.23}
\]

The number of contracts where carrier \( k \) maintains price policy zero (\( r_{k0} \)) should be high enough to permit carrier \( k \) to be evaluated in the market. Initially, carrier \( k \) is not known in the market and first values of \( \lambda_{r_{k0}} \) will fluctuate until carrier \( k \) level of service is known in the market. It is assumed that carrier \( k \) does not know exactly its level of service and that Equation (3.6) is used to update the carrier \( k \) observed level of service with a different learning rate.

After \( n_0 \) contracts applying pricing policy \( r_{k0} \), carrier \( k \) has to select a new pricing policy without an estimation for \( \partial P_{sk} (t) / \partial p_{skt} \). This new pricing policy should be randomly selected and should be close to the previous pricing policy \( r_{k0} \) to improve the estimation of \( \partial P_{sk} (t) / \partial p_{skt} \), since a secant formulation is proposed (see Equation (3.25)). Suppose that this new pricing policy is equal to \( r_{k1} \). Carrier \( k \) estimates the expected probability of winning a contract \( t \) using the following expression after \( n_1 \) using pricing policy \( r_{k1} \):

\[
P_{k,1,AFT} (r_{k1}) = P_{k,1,BEF} (r_{k1}) + \alpha_k \{ \lambda_{r_{k1}} - P_{k,1,BEF} (r_{k1}) \} \tag{3.24}
\]

where, \( P_{k,1,BEF} (r_{k1}) \) is the probability before the result of contract 1, and \( P_{k,1,AFT} (r_{k1}) \) is the probability after the result of contract 1.

With the values of \( P_{k,0,AFT} (r_{k0}) \) and \( P_{k,1,AFT} (r_{k1}) \), the value of \( \partial P_{sk} (t) / \partial p_{skt} \) for pricing policies between \( r_{k1} \) and \( r_{k0} \) can be estimated using a secant formulation, which is used to approximate the value of the derivative of functions without analytical form (Kaw and Kalu, 2008):

\[
\frac{\partial P_{sk} (t)}{\partial p_{skt}} = \frac{P_{k,1,AFT} (r_{k1}) - P_{k,0,AFT} (r_{k0})}{r_{k1} - r_{k0}} \tag{3.25}
\]

With the results from Equations (3.23) to (3.25), an optimized pricing policy and a carrier contract participation policy can be implemented using Equations (3.11)/(3.14) and Equations (3.17)/(3.18), respectively. After some different pricing policies, carrier \( k \) would be able to plot
the shape of function of the probability of a carrier $k$ winning a contract in the market given the rate proposed, $P_k(r_i)$. This function is associated with the carrier $k$ demand function and its estimation is currently performed by companies that implement revenue management policies (Talluri and van Ryzin, 2004). With various pairs of $[r_i, P_k(r_i)]$, a regression technique can be implemented for each carrier $k$ to estimate the parameters of the function given a certain shape (see Figure 3.3).

![Probability function of a carrier $k$ winning a contract in the market](image)

**Figure 3.3: Probability function of a carrier $k$ winning a contract in the market**

### 3.3. FREMIS Implementation

#### 3.3.1. Data and Surveys

FREMIS can be applied to any freight market, but its main contribution is expected to be on applications for urban freight markets, since they are usually not in a stable equilibrium (Friesz and Holguín-Veras, 2005) and agent-based modelling can better represent their market dynamics. Besides the characteristics of the transportation network, more information is necessary to permit FREMIS application in a freight modelling study.

First, some revealed or stated data from the region of study should be obtained to estimate models on the demand side: shipment bundling model and carrier selection model. A shipment
bundling model estimated using local data would permit the identification of the impact of local freight poles in the process of bundling shipments. Likewise, a carrier selection model estimated using local data would incorporate local weights for the importance of carriers’ level of service. Stated preference data is a less expensive option and its data enrichment methodologies are already consolidated in marketing studies that mitigate its main shortcoming: external validity (Louviere et al., 2000).

Second, cost parameters should also be obtained to represent the behaviour of the supply side in FREMIS. Three cost parameters are included in FREMIS carrier profit formulations, see Equations (3.10), (3.11), (3.13) and (3.14): variable cost per distance travelled by type of vehicle \( c_k^{d^w} \), fixed cost per number of vehicles by type of vehicle \( c_k^{N^w} \), and fixed cost of carrier facilities \( F(L_{SF_k}) \) (distribution centres, warehouses) combined with level of service (tracking shipments). Some publications provide information about the former two parameters (Transport Canada, 2005) and the last parameter should be obtained in a specific survey if long-run decisions are relevant in the freight modelling study.

Third, carrier level of service and the values of its attributes should be analysed in the region of study. As a consequence, a survey should be implemented to collect the values of carrier attributes (e.g. travel time reliability) in the region and to find the relationship between these attributes and transportation network characteristics (e.g. travel time variability). Identification of this relationship will permit the evaluation of the impact of changes in the transportation network using the outputs of FREMIS.

Fourth, information about the characteristics of shippers and carriers in the region have to be obtained. This information is mainly the number of shippers and carriers, number of vehicles by type, and resources owned by the companies (warehouses, distribution centres). Number of shippers and carriers can be obtained from institutions that merchandise company lists and number of vehicles can be inferred from surveys such as the Canadian Vehicle Survey (Statistics Canada, 2009). Information describing the resources available to companies is more challenging to obtain and will probably require a specific data collection procedure.
3.3.2. **Calibration and Validation**

There are some parameters in FREMIS that may need to be calibrated using secondary data (e.g. traffic counts, commodities surveys, roadside surveys) such as:

- Scale parameters in demand models;
- Learning rate parameters;
- Distributions of cost parameters: e.g. normal, lognormal;

The procedure to calibrate and validate FREMIS is not currently developed. The main requirement for the calibration / validation of FREMIS is that secondary data should have more than one observation. Transportation surveys usually collect information for a “typical” day (one observation) and this information is used in the development of demand models (Órtuzar and Willumsen, 2011). This information is not suitable for the FREMIS calibration/validation because one observation is only one realization of the simulation system and it does not provide information for the estimation of calibration parameters. Multiple observations are required to permit the estimation of mean and standard deviation of observed and simulated values and to consequently definition of calibration parameters.

3.3.3. **Supply Side: Carriers’ Price Strategy and Rational Behaviour**

The assumption of rational behaviour (maximization of expected profit function) in the supply side is required to formulate the equations presented in Section 3.2.2. This assumption is analyzed in this section and a discussion is presented on how FREMIS formulation can be extended to accommodate other hypotheses for carriers’ behaviour.

The rational behaviour assumption is used in much of microeconomic theory (Mas-Colell, Whinston and Green, 1995) in areas such as Consumer Theory, Game Theory, Contract Theory, and Theory of Industrial Organization. The models formulated using the rational behaviour assumption are, at the same time, normative (used to define how agents should behave to maximize their benefits) and predictive (used to predict how agents behave) models. These models are developed using mathematical formulations for the maximization of utility/profit functions based on some agents’ actions (e.g. price strategy, consumption of products).
This approach was adopted in Section 3.2.2 to derive Equations (3.11) and (3.14), which consist of carrier bid dynamic models (pricing strategy) for shipment contracts based on operating cost parameters ($/km per type of vehicle), fleet of vehicles (number of vehicle per type), required delivery network for the contract (distance to deliver the shipments in the contract) and information about the competition (probability of winning a contract) in the supply side (carriers). The assumption that carriers in a freight market are developing their price strategy using Equations (3.11) and (3.14) is probably not valid for all of them. However, price strategies based on profit maximization might become more regular in freight markets since some recent publications proposed pricing models to maximize profit for carriers (e.g. Lee, Kwon and Ma, 2007; Friesz et al, 2008; Chen et al, 2009; Schönberger and Kopfer, 2012) and, according to Talluri and VanRyzin (2004), freight transport presents some factors (e.g. product differentiation and capacity and time constraints) which can result in higher benefits with the adoption of revenue management strategies.

In the trucking industry, however, prices are usually defined based on freight rates ($/km or $/km/kg) calculated using cost information, average distance (in km) travelled per period (e.g. day, week, month) and capacity of vehicles (in kg) (Emmett, 2009). This approach is called cost-plus pricing in marketing literature and it is the most common pricing strategy because of finance prudence, even though it is considered (Nagle, Higan, and Zale, 2011, p. 2): “a blueprint for mediocre financial performance”. The main shortcoming of this strategy is caused by the relationship that price has with demand and, since cost-plus pricing does not consider the demand, this strategy would sometimes result in unreasonable behaviour by companies. For instance, suppose that a trucking company has a decreasing demand (average distance travelled) and the same fixed costs. Adopting cost-plus pricing, they would increase freight rates, which is the opposite of the recommended strategy for a company in this situation (Nagle, Higan, and Zale, 2011) because they would probably lose more demand with this approach.

FREMIS can be adapted to permit that some carriers use cost-plus pricing or some other hybrid pricing strategies. For instance, in Equation (3.14), there are two components in the right side of the equation: a cost term and a competition term. To permit some carriers to have these two other strategies, a parameter $\lambda_k$ ($0 \leq \lambda_k \leq 1$) for each carrier $k$ should be included in Equation
The possible pricing strategies using Equation (3.24) are: (1) cost-plus pricing: $\lambda_k = 0$; (2) hybrid approach: $0 < \lambda_k < 1$; (3) profit maximization: $\lambda_k = 1$. The $\lambda_k$ parameter

$$p_{skt} = \left[ \frac{\sum_{w=1}^{W} c_k^d w \delta_{wt} W T H - \sum_{w=1}^{W} c_k^d w \delta_{kt} w}{\text{Cost Term}} \right] - \alpha_k \left( \frac{P_{sk}(t)}{\partial P_{sk}(t)/\partial p_{sk}} \right)$$

(3.26)

Another pricing strategy that can be used in FREMIS is the price follower strategy. Companies adopting this strategy, called followers, set their prices based on the price of a small group of companies, called leaders (Ono, 1982). For instance, if some carriers know the prices of leaders in the market, they can set their prices lower than the reference company to increase the probability of winning the contract. The price follower strategy can be implemented in FREMIS by calculating the average of recent price values from L carrier leaders in the market, see Equation (3.27).

$$p_{skt} = \frac{\sum_{l=1}^{L} p_{sbt}}{L}$$

(3.27)

There is a number of factors that facilitates the existence and identification of the price leader (Mago and Dechenau, 2009), such as differences in firms’ risk attitudes, informational asymmetries, brand loyalty, product differentiation, heterogeneous production costs and firm size (production capacity). The analysis of the major factors in freight markets that should be considered in FREMIS implementation is the subject of future research.

Market structure may also influence some carriers to follow a certain price value. In competitive markets conditions, carriers’ price strategy would follow the marginal costs of a contract $t$ (see Equation (3.28)), while in a monopoly market (with only one carrier), carrier’s price strategy would follow the expression presented in Equation (3.29), where price is a function of the elasticity of demand (Equation (3.30)) and marginal cost (Varian, 1992). The values presented in Equations (3.28) and (3.29) may be used by some carriers instead of the value presented in Equation (3.27).
\[ p_{skt} = \frac{dC(Y)}{dY_t} \]  
\[ p_{skt} = \left(1 + \frac{1}{\epsilon(Y)}\right)^{-1} \frac{dC(Y)}{dY_t} \]  
\[ \epsilon(Y) = \frac{p_{skt}}{Y} \frac{dY}{dp_{skt}} \]

where:
- \( Y \): vector of the output of a carrier in the market – set of flows
- \( Y_t \): vector of the output of a carrier in the contract \( t \) – set of flows
- \( C(Y) \): cost of carrier as function of the output \( Y \) in the market

Equations (3.11) and (3.14) were derived using expected profit formulations. Since 1979 with the development of prospect theory (Kahneman and Tversky, 1979), an approach using value and weighting functions instead of changes in profit and expected value, respectively, is suggested seeking to better represent agents’ behaviour. The application of prospect theory in FREMIS is also the subject of future research because it requires the collection of data of agents’ behaviour in risky situations. A discussion on how FREMIS can be adapted to incorporate prospect theory is presented next.

Value functions are used to represent the utility for different values of profit (gain and losses) based on the situation of agents (e.g. profit margin). For instance, a carrier who is performing badly in the market (low profit margin) would give more value to a profit from a contract than carriers who are performing well. To apply prospect theory, profit values in Equations (3.12) and (3.13) would require the adoption of a value function of changes in profit (\( \Delta \pi \)) and current profit level (\( \pi_0 \)): \( v(\Delta \pi, \pi_0) \).

Weighting functions, \( w(\cdot) \), are used to represent different perceptions by agents in the probability (\( p \)) of some outcome. These perceptions are used by them when deciding the action to perform in risky situations. As a consequence, the expected profit formulation, \( p_1 \pi_1 + (1-p_1)\pi_2 \), should be substitute by a weighted profit formulation: \( \epsilon(p_1)\pi_1 + w(1-p_1)\pi_2 \).
3.3.4. Transactions and Contracts

Another required extension to implement FREMIS is the representation of how shippers search for carriers in the market. In contract theory (Bolton and Dewatripoint, 2005), two types of approaches are analyzed: screening and signalling. Screening is used to represent the processes when shippers screen carriers to select the “best” one. Examples of screening processes are traditional auctions and requests for proposals. Signalling is used to represent the processes when carriers send information (a signal) to shippers to show that they are the “best” one. One example of signalling is any type of advertisement that a carrier uses.

The main relevant aspect in the representation of transactions in a market is to identify how agents contact each other. For instance, based on 2006 InfoCanada database there are 12,957 manufacturing companies (shippers) and 2,499 motor-freight carriers located at Greater Toronto and Hamilton Area (See Chapter 4). Therefore, there are many possibilities of contact for shippers and carriers in each transaction. In FREMIS formulation, the assumption is that shippers are obtaining information about carriers’ level of service while interacting in the market, see Equation (3.6). To obtain this information, shippers have to explore the market (using screening or signalling processes) which can be represented by using a $\epsilon$-greedy exploration method combined with Equation (3.6).

Another approach that can be used is to create 3PL agents in the simulation. The main objective of a 3PL company is to provide services of matching shippers and carriers in the freight market in an optimized way. Therefore, a 3PL company in FREMIS would substitute the participation of a shipper in the market by collecting information about carriers’ level of service, using Equation (3.6), carrier’s delivery capacity and select carriers for each contract of shipments (after bundling shipments). The performance of 3PL companies would be measured by shippers’ level of utility and carriers’ profit who contracted them, consequently, their profit should be a function of these values. The inclusion of 3PL in future FREMIS simulation will require a specific survey with 3PL companies.

When interacting in the market, shippers have to decide about length of contracts. Based on the literature, length of contract of shipments is usually between one and two years for large
shippers (Sheffi, 2004) and carriers are usually required to guarantee capacity on demand with a defined rate but shippers are not required to use their services for a minimum demand (Talluri and Ryzin, 2004). If shippers obtained a lower price in the spot market, they bypass their contract carriers (Talluri and Ryzin, 2004). For other types of shippers, small and medium, there is not a defined length of contract.

3.4. Concluding Remarks

The framework presented in this chapter incorporates three important elements of the freight market: product differentiation, economies of scale/scope, and agent interactions. Product differentiation is incorporated in the demand side with a utility-based formulation and in the supply side with a pricing strategy based on carriers’ cost and the probability of being selected in a contract. Economies of scope/scale are incorporated in the demand side with the shipment bundling model and in the supply side by a cost formulation for each new contract using, for instance, vehicle routing algorithms.

Agent interactions are represented using learning processes (e.g. Q-learning) assuming that agents obtain information about the market while performing transactions (interacting). The framework proposes the utilization of Q-learning approaches to represent the processes by which shippers identify carrier level of service in the market and the expected probability of a carrier winning a contract. These elements are used in the carrier selection model and in the carrier bid expression, respectively. The last component of the framework is a secant formulation, based on numerical methods, to estimate the rate of change of the probability of a carrier winning a contract with respect to carrier bids.

Current urban freight simulation models, which are mostly developed using the approach Hunt and Stefan (2007), do not have these characteristics. The application of FREMIS in urban freight simulation would permit the analysis of the impact of market dynamics in the freight flows and also the conditions by which the urban freight market achieve equilibrium, see Friesz and Holguín-Veras, 2005 for a discussion of equilibrium in urban freight market.
Most current agent-based freight simulation models also do not have an explicit representation of agent’s competitive behaviour in the market. Using FREMIS, many aspects related to agent’s competition can be analysed such as company size/market-share (bigger companies have more opportunities for economies of scope/scale) and the impact of changes in the transportation system (e.g. new facilities) in agent’s behaviour (e.g. changes in level of service for some carriers). These aspects might impact the output of freight markets, freight flows, and current models are not sensitive to changes in agent’s competitive behaviour.
Chapter 4

GTHA Freight Market: Description and Data

Based on previous chapter, each FREMIS implementation depends on the following information for the freight market under study:

i) demand models, see Equations (3.1) to (3.4) in Chapter 3: shipment bundling model and carrier selection model

ii) Carrier service attribute values (used in carrier selection model and carrier bid functions of FREMIS): e.g. travel time reliability

iii) Costs parameters in profit and carrier bid functions, see Equations (3.10) to (3.18) in Chapter 3: cost by distance travelled and fixed cost by number of vehicles per type of vehicle, and fixed cost of carrier facilities (distribution centres, warehouses) for a certain level of service (e.g. shipments tracking systems)

iv) Characteristics of shipper and carriers in the region: number of shippers and carriers, their economic characteristics (e.g. sales volume, number of employees), and ideally, companies resources (distribution centres, warehouses, fleet of vehicles, shipments tracking shipments)

The freight market selected for the first FREMIS implementation is the Greater Toronto and Hamilton Area (GTHA) freight market (see Figure 4.1). This market is defined for the research by one of its outputs: freight flows. It is considered that freight flows of this market are composed of: (1) GTHA internal freight flows (2) freight flows with either origin or destination in the GTHA. This market was the focus of a recent study, Metrolinx (2011). The GTHA and this market are described and characterized in the first part of this chapter using aggregate information.
Some of the FREMIS elements can be obtained from secondary data. The following references of secondary data provide information for Ontario and GTHA and they can be used for the GTHA FREMIS simulation:

\( i \) Costs parameters by type of vehicle: Transport Canada (2005)

\( ii \) Shippers and carriers and their economic characteristics (sales volume): InfoCanada database

\( iii \) Number of vehicles by type: 2009 Canadian Vehicle Survey

The remaining elements (demand models and carrier attributes) required for FREMIS implementation on GTHA Freight Market Simulation were obtained using a customized web survey. The survey methodology and some initial results are forthcoming in a publication (Cavalcante and Roorda, 2013). The sample of this survey was composed of companies (shippers and carriers) located in the GTHA that are currently interacting in the freight market (performing transactions). Data obtained for demand models are classified as stated preference data since respondents are presented with hypothetical situations and asked to make choices indicating their preferences. The final part of this chapter presents major results of this survey. Demand models specifications and results are presented in Chapters 5 and 6.

4.1. GTHA Freight Market

The Greater Toronto and Hamilton Area (GTHA) is composed of eight cities (Brampton, Burlington, Hamilton, Mississauga, Oshawa, Pickering, Toronto and Vaughan), fourteen towns (Ajax, Aurora, Caledon, Clarington, East Gwillimbury, Georgina, Halton Hills, Markham, Milton, Newmarket, Oakville, Richmond Hill, Whitby and Whitchurch-Stouffville) and four townships (Brock, King, Scugog and Uxbridge). Their locations and the location of the main highways in the GTHA region are visualized in Figure 4.1. The GTHA had a population of 6 million people in Census 2006\(^1\) or 19.2% of Canada’s population.

\(^1\) Even though Census 2011 is already available, Census 2006 is used on this Chapter because InfoCanada database is from 2006.
Figure 4.1: GTHA region

Freight transportation demand is influenced by population and companies’ location (Cambridge Systematics, 1996 and 2007). Using the 2006 InfoCanada business establishment database combined with Census 2006, a concentration of population and companies is identified in GTHA West region (darkest gray areas in Figure 4.1) and in the City of Toronto: they have
approximately 80% of population and companies, but comprise only 55% of GTHA area (see Figure 4.2).

![Figure 4.2: GTHA Proportions – Population, Number of Companies and Area](image)

The concentration of population and companies across the GTHA is not uniform. Locations closer to Toronto have a higher concentration (population and companies) and this is demonstrated by Figure 4.3 which presents two concentration measures by GTHA locations: population density (population / area in km²) and company density (number of companies / area in km²). GTHA locations in the horizontal axis are displayed in the following way. West locations are displayed on the left, east locations on the right and Toronto divides west and east locations. Locations are arranged in ascending order of road distance to/from Toronto. For instance, Mississauga is the closest west location to Toronto and, consequently, is displayed on the left of Toronto. Figure 4.3 shows a relationship between locations of population and
companies.

Figure 4.3: Population and Companies Concentration in the GTHA

The location of companies and population is also interconnected to the location of GTHA highway network, see Figure 4.4. Approximately, 95% of GTHA companies are located within 5km distance of GTHA highway network and, most of GTHA freight movements may be located inside this region (see Figure 4.5), which represents 54% of total GTHA area, if the majority of freight movements occur between companies.
Few references were identified with an estimation of freight movements in GTHA freight market (Roorda et al., 2010; MITL, 2010). MITL (2010) is the most complete study of freight movements in the GTHA and it is used on this research to characterize GTHA freight market. MITL (2010) estimated origin-destination (O-D) matrices of commercial vehicle movements for light, medium and heavy commercial vehicles. Three main types of urban commercial vehicle movements were defined:

i) Tour-based movements: commercial vehicles (light, medium or heavy) leaving establishments to deliver/pick up goods or provide services. A microsimulation framework by firm level was applied to model tour-based movements and the framework is based on Hunt and Stefan (2007).

ii) Fleet allocator: commercial vehicles used to cover a territory within an urban area providing services such as mail delivery, courier services, garbage and recycling pick up. A regression model developed for Edmonton was transferred to estimate light, medium and heavy vehicle total fleet-allocator trips generated. A spatial interaction model with locally inferred parameters was used in the trip distribution phase.

iii) Internal-External movements: vehicle movements where either origin or destination is located outside GTHA area. These movements were estimated using 2006 MTO Commercial Vehicle Survey.
A summary of GTHA freight demand estimated in MITL (2010) is presented in Figure 4.6. Tour-based movements represented approximately 70% of vehicle movements in MITL study. Since FREMIS framework is capable of incorporating tour decisions using price functions based on operational aspects (total distance travelled), see Equations (3.11) and (3.14), a GTHA FREMIS implementation would be able to represent satisfactorily a major share of GTHA freight demand. The total number of freight trips obtained in MITL study, approx. 2.0 million freight trips / day, represents 330 vehicle trips per 1000 people per day in the GTHA. According
to World Bank (2009), some data on urban freight converge and the number of vehicle trips per 1000 people per day varies from 300 to 400 vehicle trips.

Figure 4.6: Daily GTHA Commercial Vehicle Trips – MITL (2010)

4.2. Customized Web Survey

4.2.1. Predictive Behavioural Models: Data Collection Methods

There are two methods that can be used to collect data for disaggregate behavioural models (Louviere et al., 2000): stated preference (SP) and revealed preference (RP). RP methods are used to obtain information about the actual behaviour decision makers while SP methods refer to a family of techniques that collect preferences of decision makers when facing hypothetical choice scenarios.

RP data are usually preferred for the analysis of decision makers’ choices because such data are associated with actual market decisions. However, the literature suggests adopting other techniques to address some problems found during the utilization of RP data, such as (Pearmain and Kroes, 1990):
Actual behaviour of the market (choices) may not vary sufficiently to estimate accurate statistical models and explanatory variables may also be correlated.

Actual behaviour may reflect factors that are not the main focus of the analyst such as new products/services/policies evaluations.

Required sample size for RP data may be very large resulting in high survey costs.

RP data collection may not be suitable for preferences that respondents are not willing to divulge such as related to socially unaccepted behaviour or to companies’ strategic decisions.

SP methods were developed in marketing research area in the beginning of 1970s and they refer to all methods where respondents state their preferences in hypothetical situations. SP methods have various characteristics that promote their adoption in modelling decision makers’ choices, such as (Pearmain and Kroes, 1990):

1. It is possible to guarantee a minimum accuracy level for the statistical models because the analyst can control alternatives presented to respondents.
2. Collinearity between variables can be reduced because the experiment is designed by the analyst.
3. New products/policies can only be analysed in a quantitative way using SP data.
4. The required sample size is usually smaller than in the case of RP data because one respondent can generate more than one observation in the sample.
5. When RP data are proprietary, for example when respondents provide private information about their companies, SP methods are one of the few methods to obtain some information about the preferences of decision makers.

The main disadvantage of SP methods is the lack of external validity. Since respondents provide responses in hypothetical scenarios, models derived from SP data may not reflect actual behaviour. The most commonly used SP methods are conjoint analysis, functional measure, trade-off analysis, and transfer-price method (Pearmain and Kroes, 1990). In transport applications, conjoint analysis method is regularly applied and is adopted in this survey. The transfer-price method is also used in some transport applications when the analyst asks respondent’s willingness to pay for a certain improvement in the transportation system (MVA Consultancy, 1994).
The first phase of the experimental design of a SP survey consists of defining:

1) number of choice sets

2) number of alternatives in each choice set

3) the attributes of the alternatives in each choice set

4) the levels of the attributes of the alternatives in each choice set

In most studies respondents evaluate between one and sixteen choice sets (Louviere et al., 2000), a minimum of three and a maximum of seven attributes should be used to represent more realistic and less complex choice situations (Pearmain and Kroes, 1990). Besides that, attributes should have more than two levels to permit the analysis of non-linear utility functions. The values of the attributes should:

- be reasonable
- be related to the experience of the respondents
- permit that alternatives compete with each other

After the first phase, it is possible to list all options that may be presented to a respondent. For the case of $m$ attributes, $A_1, \ldots, A_m$, and number of levels of the $k$th attribute is $l_k$, where $l_k \geq 2$ for $k = 1, 2, \ldots, m$, the total number of options is $l_1 \times l_2 \times \ldots \times l_m$. In traditional experimental design, the design that compounds all possible options is called complete factorial design. The complete factorial design has two important characteristics: all attributes (or factors) are orthogonal with each other (correlation between them is zero) and all the effects of the attributes (main effects and interaction effects) can be estimated. A main effect of an attribute is the average effect of an individual attribute over the response while an interaction effect is the joint average effect of the values of two or more attributes over the response.

The complete factorial design is very difficult to implement in a SP survey because the number of options generated is very large. To reduce the number of options, Pearmain and Kroes (1990) suggest four approaches of which the first and fourth are more commonly used:

- Eliminate the dominated and dominant options
- Block the design by value of attribute by dividing the experiment into two or more experiments and maintain at least one attribute, usually the most important one, in all
experiments. These experiments should be randomly selected before presented to a respondent

- When the number of attributes is high, divide the whole experiment into a series of experiments and keep one common attribute in all the experiments
- Use fractional factorial designs

Fractional factorial design is a subset of the factorial design set that maintains some defined statistical characteristics (e.g. orthogonality) but some attributes effects cannot be estimated, especially interaction effects. The selection of which fractional factorial design should be adopted depends on the orders of the interaction effects that are relevant in the study. Studies in transportation discrete models detected that (Louviere et al., 2000):

- the main effects contribute from 70 to 90% of the estimated variance
- second order interaction effects (two attributes involved) contribute from 5 to 15% of the estimated variance
- higher order interaction effects contribute to the remaining estimated variance

Analysing the advantages and disadvantages of RP and SP methods, researchers identified that the combination of both types of data in a forecasting model will result in more accurate results because usually one advantage of a method is the counterpoint of a disadvantage of the other method (e.g. SP – orthogonal statistical designs and RP – variables correlation). The process of combining both sources of data is called data enrichment (Louviere et al., 2000). There are two approaches in the literature:

- Morikawa (1989): based on calibration of scale factors, e.g. $\mu_B$ in Equation (3.1). This approach assumes that respondents answer SP surveys using a different scale for the random term of the utility function: either providing answers with more certainty (lower variance and higher scale) or less certainty (higher variance and lower scale). As a consequence, SP and RP estimates of trade-offs of attributes (e.g. value of time), $\beta_1/\beta_2$, are both assumed to be consistent

- Swait et al. (1994): based on alternative specific constants. This approach assumes that respondents provide different answers in SP surveys regarding the unobserved attributes of
alternatives, represented by alternative specific constants. This approach assumes that only SP trade-offs are valid and that RP data represent current market share information.

An approach has to be selected in the calibration process for GTHA FREMIS implementation since predictive models are based on SP data. Morikawa’s approach is more appropriate because it can be used for unlabelled alternatives (carriers in FREMIS), which removes the requirement of identifying some carriers (e.g. FedEx or Purolator) in the freight market to measure their alternative specific constants. The FREMIS formulation was developed assuming Morikawa’s approach in the calibration process. Swait’s approach would require the inclusion of alternative specific constants in the carrier selection model, see Equations (3.2) to (3.4), and the identification of carriers (e.g. FedEx or Purolator) in another SP experiment.

4.2.2. Survey Sampling

The survey population of this project is composed of shippers and carriers that interact in the freight market and are located in the Greater Toronto and Hamilton Area (GTHA). Some companies may be shippers, but are not active (no transactions or interactions) in the freight market, because they have their own private fleet and deliver their shipments. These companies are not part of the survey population, because they do not interact in the freight market.

This survey focused on three groups of companies: Manufacturing (mainly shippers), Wholesale (shippers or carriers) and Motor-Freight Carrier (mainly carriers). These groups are classified using 2 digits of the Standard Industry Classification (SIC) codes. The selection of these groups is based on the fact that they likely generate a large share of total commodity flows in the GTHA.

A database of companies obtained in the summer of 2009 from InfoCanada, a Canadian provider of business and consumer databases, was available. Based on this database, the number of companies for each group was: (1) Manufacturing: 12,957 (2) Wholesale: 12,665 (3) Motor-Freight Carrier: 2,499. A stratified sampling procedure was implemented using annual sales
volume and number of employees to define the strata. The minimum sample size was calculated using the formulation for minimum sample size in proportion\(^2\) (assuming maximum variance, \(p = 0.50\)) with 95% confidence (\(Z = 1.96\)) and 5% error (\(\varepsilon\)) (Cochran, 1977): 384 observations per type of respondent (shipper or carrier). In each model, at least four observations (decisions) per respondent are expected, therefore the minimum sample size for shippers’ survey is 100. As a result, the target sample size is 200 companies in total: 100 shippers and 100 carriers.

The data were collected using a self-respondent web-survey. Based on Dillman et al. (2009), the response rate was expected to be between 5 and 25%. Using an effective response rate of 10% (i.e. the rate based only on companies that are successfully contacted) and assuming that 50% of the companies in the database would not be contacted or eligible to participate in the survey (not active in the shipper-carrier market), the minimum number of companies included in the sample was 4,000: 2,000 shippers and 2,000 carriers. To guarantee a good representation for each group in the sample, avoiding the underrepresentation of motor-freight carriers, the sample was equally divided between the three groups: about 1,333 companies in each group.

The sample of companies was distributed among strata using initially the same sample fraction (sample size / population size) for each stratum in a group: (1) Manufacturing: \(1,333/12,957 = 10.3\%\) (2) Wholesale: \(1,333/12,665 = 10.5\%\) (3) Motor-Freight Carrier: \(1,333/2,499 = 53.3\%\). The number of companies in the sample in each stratum was rounded up to guarantee at least one company for each stratum, resulting in a different sample fraction per stratum (see Table 4.1 to 4.3). The total number of companies in the sample for the survey was 4,043 companies.

\[ n_p = \frac{Z^2 \times p \times (1-p)}{\varepsilon^2} = \frac{1.96^2 \times 0.5 \times 0.5}{0.05^2} = 384 \]
Table 4.1: Sample Fraction per Stratum: Manufacturing

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<th>Number of Employees \ Sales Volume</th>
<th>No Information</th>
<th>Less Than $500,000</th>
<th>$500,000-$1 Million</th>
<th>$1-2.5 Million</th>
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Table 4.2: Sample Fraction per Stratum: Motor Freight Carriers

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Sales volume values were used to validate the sampling strategy since they are intrinsically related to freight movements (Cambridge Systematics, 2007). The distributions of the number of companies by sales volume in the population and in the sample are very similar (see Figure 4.7, Figure 4.8 and Figure 4.9) and consequently the sampling strategy was able to represent the population.

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<tr>
<th>Number of Employees \ Sales Volume</th>
<th>No Information</th>
<th>Less Than $500,000</th>
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Figure 4.7: Distribution Sales Volume: Sample / Population - Manufacturing Companies

Figure 4.8: Distribution Sales Volume: Sample / Population - Motor Freight Carriers
4.2.3. Survey Questions and Models

The main objectives of this survey are the collection of data for the development of demand models in FREMIS: shipment bundling model and carrier selection model. Besides that, carrier attributes values are also collected and analysed and agent characteristics are also collected (e.g. type of carrier selection process).

The Total Design Method proposed by Dillman et al. (2009) was adopted for the design of survey questions. This method proposes that three approaches should be used to maximize survey response: minimize the costs for responding, maximize the rewards for doing so, and establish trust that those rewards will be delivered. Response costs were minimized by limiting survey questions for each respondent based on their characteristics.

Questions were classified in three types (see Figure 4.10): questions presented to all respondents, questions presented only to carriers (with a character “C” on the survey index) and questions presented only to shippers (with a character “S” on the survey index). As a
consequence, there are two surveys embedded in the web survey: shippers’ survey and carriers’ survey. These questions were organized using a logical sequence (e.g. simpler questions presented first and complex questions later) and they were shown to each respondent based on respondent’s answers during the survey (see Figure 4.10). See in Appendix 1, questions used and descriptive statistics for the survey.

The survey starts with a question to identify shippers and carriers, question 1 (Q1) in Figure 4.10, and based on their answer, respondents are presented their respective survey. Both surveys (carriers and shippers) start with the same question regarding how carriers are selected in the freight market, question 1C (Q1C) and question 1S (Q1S): by price or by price and other attributes (e.g. time reliability). This information is important because FREMIS is developed with the assumption of product differentiation (carrier selected by price and others attributes) and, as a consequence, the SP experiment, question 4S (Q4S), should only be applied to shippers who answered price and other attributes in Q1S.

Next, a question for both shippers and carriers is used to collect information of one shipment in the company, questions 2C (Q2C) and question 2S (Q2S), respectively. This shipment is used in Q4C in the carriers’ survey and it is also used to collect some information related to freight rates, travel time, and outsourcing, which can be used in the validation/calibration of FREMIS GTHA implementation.

After the shipment question, the following questions are specific to each type of survey. In question 3C (Q3C), carriers are asked to provide values of their attributes such as time reliability, shipments loss/damage and driver’s quality. This question is only presented to carriers that answered “Price and Others” in Q1C. The assumption is that carriers that compete only on price would not provide accurate values for their service attributes because they do not consider them relevant. Carriers attributes included in Q3C were selected using a literature review of most relevant carriers attributes in urban logistics services (Lambert et al., 1993; Crum and Allen, 1997; Murphy et al., 1997; Kent et al., 2001; Voss et al., 2006; Fowkes, 2007; Meixell and Norbis, 2008). Data collected on Q3C can be used in the FREMIS formulation (see Section 4.2.6).
Figure 4.10: Survey Questions – Flow Chart
After Q3C, carriers are presented with an experimental auction question. Information from Q2C is used to form hypothetical contracts and carriers are asked to indicate if their company would be interested in presenting a bid for the contract, the value of their bid, and are asked to provide an estimate of the probability of their company winning this contract. This question may be the subject of future research related to GTHA carrier competition. The last question in carriers’ survey, question 5C (Q5C), is used to collect type of operations by carriers, e.g. truck operations (parcel, less-than-truckload and truckload shipments).

Meanwhile, shippers start their specific survey with Question 3S (Q3S). This question asks shippers to provide their level of importance for some carriers’ attributes, which are the same levels used in Q3C, in a 5-level Likert scale: from 1 – Unimportant to 5 – Very Important. Attributes ranked at level 4 (Important) or 5 (Very Important) are included in the SP experiment in question 4S (Q4S). This approach was implemented to minimize non-atttendance bias (Hensher and Greene, 2010), which occurs when an attribute included in a SP survey is not considered by respondents in the decision process. In Q4S, shippers are asked to select carriers given their service attributes in a SP experiment. More information about this experiment is provided in Chapter 6.

Then, shippers are asked to provide their level in the supply chain (1 indicates closer to end-consumer, and 5 indicates closer to raw-materials supplier) in question 5S (Q5S). The last question in shippers’ survey asks them to provide their type of operations, question 6S (Q6S), e.g. manufacturer, after-market spare parts provider and raw materials suppliers.

After Q5C and Q6S, respondents (shippers and carriers) are presented the same questions until the end of the survey. The first question, question 2 (Q2), is presented only for a sample of respondents (carriers and shippers) based on a random number generated dynamically (probability of showing Q2 ≈ 0.50). This approach was adopted to restrict the sample to a similar sample size to the carrier selection model and to have a similar level of accuracy for the models. As a consequence, models would have a similar predictive capability in the FREMIS simulation. This question is used for the shipment bundling model. Even though this model is a
shipper’s model in the FREMIS framework, the survey question collects data from both type of respondents (or agents) to represent their perception of the freight market.

The last three questions, questions Q3, Q4 and Q5, are used to collect information describing the number of employees and sales volume, necessary to compare to population characteristics. The final question asked the respondent whether they want to participate in a draw for an incentive (a $50 gift card with 1 in 20 winning odds).

4.2.4. Implementation

The first stage was the development of a programming code for the survey since the customization requirements exceeded the limitations of available survey design websites. Several web technologies were used in the website design. Javascript was used to provide dynamic behaviour in the webpage, PHP and Ajax were used to exchange information between the server and the webpage in an efficient and dynamic way, and MySQL was used to store the data. Various drafts were developed and pilot tests were conducted to improve the quality of the web-survey.

The second stage was the recruitment process. This stage was composed of two parts: postcards and phone calls. Postcards were prepared and sent to all 4,043 companies in the database. The reason for sending postcards was to inform companies about the survey before they received phone calls. This approach was used to increase the response rate (Dillman et al., 2009). A marketing research company conducted the phone calls, which started about one week after sending the postcards. A script was provided to the marketing research company so that they would be able to: find the appropriate respondent in the company (responsible for logistics / supply chain services), screen the respondent (if a shipper, check if the shipper delivers or outsources its deliveries of shipments, i.e. the company is active if interacting in the market), inform the respondent about the survey and ask for their participation. If the respondent agreed to participate, an email was sent with more information and a link to the survey. With this approach, companies that answered or did not answer the survey were identified using an ID embedded in the web link. Respondent identification was used only to restrict reminder emails only for survey nonrespondents and it was discarded after survey completion.
4.2.5. **Response Analysis**

The survey started in mid-April, 2011, and was completed in June, 2011. The results of the phone calls are presented in Table 2. In 49% of the cases, the marketing research company was not able to contact or to identify the respondent in the company. 21% of the companies for which a respondent was identified were not included because they were not part of the survey population (mainly shippers that were not active in the market).

**Table 4.4: Recruitment Results**

<table>
<thead>
<tr>
<th>Description</th>
<th>Number of Companies</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recruited</td>
<td>431</td>
<td>11%</td>
</tr>
<tr>
<td>Refused to participate</td>
<td>763</td>
<td>19%</td>
</tr>
<tr>
<td>Wrong phone number</td>
<td>1,049</td>
<td>26%</td>
</tr>
<tr>
<td>Active calls and call-backs: not able to talk to</td>
<td>955</td>
<td>23%</td>
</tr>
<tr>
<td>the appropriate respondent</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-qualifier</td>
<td>845</td>
<td>21%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>4,043</strong></td>
<td>100%</td>
</tr>
</tbody>
</table>

About 30% of the companies (1,194) were successfully contacted and they were part of the survey population. 36% of those agreed to participate and received an email (431 companies).

Some of these companies did not start or complete the survey. Using an adapted approach based on Bethlehem et al. (2011), the response of the recruitment process and web-survey can be analysed based on the following stages:

1) **Contact**: companies that the marketing research company was able to contact
2) **Eligible**: companies that are in the survey population
3) **Agrees to participate**: companies that were recruited
4) **Participates**: companies that started the survey
5) **Completes**: companies that completed the survey

Based on the outcome of these stages, non-respondent companies in the survey can be classified, in statistical terms (Bethlehem et al., 2011), as non-response, which may result in an error in the models, or as overcoverage, which represents that the initial sample had companies that were not eligible to participate in the survey, i.e. companies that are not active in the freight market.
A flow-chart with the response results of the survey is presented in Figure 4.11. The percentage represents the percentage of companies per group in the output of each stage (a cumulative percentage is presented close to the last box, “Response”). For instance, of the companies, which were contacted, 42% of manufacturing companies (SIC 2-digit 20-39) were not eligible to participate in the survey while 58% were eligible to participate.

Apparently, there was not a tendency of nonresponse/overcoverage by type of company: the proportions of “yes” or “no” for each stage are very similar. The only exception is the last stage: if companies did not complete the survey. Motor freight carriers were proportionally less able to finish the survey, only 37%, when compared with other types of companies, 62% for manufacturing companies and 57% for wholesale companies. This difference was a consequence of the different complexity between answering carriers’ survey and shippers’ survey. The main difference occurred in the most challenging question in each survey: Questions Q4C and Q4S. While only 2% of respondents who started Q4S did not answer it, 15% in Q4C did not answer. As a consequence, data in Question Q4C were not used in this research to avoid bias in the analysis.

With the definitions used by Bethlehem et al. (2011), the response rate can be defined as the proportion of eligible contacts in the sample that completed the questionnaire (using proportions in Figure 4.11):

i) manufacturing: $0.39 \times 0.57 \times 0.62 = 0.138$ or 13.8%

ii) wholesale: $0.33 \times 0.57 \times 0.57 = 0.107$ or 10.7%

iii) motor freight carrier: $0.36 \times 0.58 \times 0.37 = 0.077$ or 7.7%

In the end, 129 companies fully completed the questionnaire. The final number of observations available is 83 shippers and 66 carriers. Even though the response rate is at the lower end of what was expected (5 to 25%), low response rates for web-based SP surveys in freight are not uncommon. In the Fall/2005, Patterson et al. (2010) obtained a total response rate of 5.4% (392 responses out of 7,229 companies) for a more restricted survey population (companies with more than 50 employees) in the Quebec–Windsor corridor. Patterson et al. (2010) did not identify whether the 7,229 companies were eligible companies or not.
Figure 4.11: Survey Response
4.2.6. Carriers’ Attributes Values

Carriers’ attributes values were collected in question 3C (Q3C), see Figure 4.12. The statistics presented in this section should not be used directly since the sample size is small (approximately 70 carriers).

The order of the attributes presented to carriers was randomly defined for each respondent. This procedure is used to randomize bias provoked by respondent answering top or bottom questions differently (Dillman et al., 2009). Ten carrier attributes were included, which can be classified in four types, see Table 4.5.

<table>
<thead>
<tr>
<th>Attribute Types</th>
<th>Number of Attributes</th>
<th>Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrier general evaluation/reputation in the market</td>
<td>2</td>
<td>– General evaluation of the carrier by the shippers</td>
</tr>
<tr>
<td></td>
<td></td>
<td>– Reputation of the carrier in the market</td>
</tr>
<tr>
<td>Attributes related to the transportation system</td>
<td>3</td>
<td>– Delivery reliability of the carrier</td>
</tr>
<tr>
<td></td>
<td></td>
<td>– Quality of the drivers of the carrier</td>
</tr>
<tr>
<td></td>
<td></td>
<td>– Loss / damage of products during deliveries of the carrier</td>
</tr>
<tr>
<td>Price</td>
<td>1</td>
<td>– Pricing of the carrier</td>
</tr>
<tr>
<td>Other attributes</td>
<td>4</td>
<td>– Follow-up by the carrier on service complaints</td>
</tr>
<tr>
<td></td>
<td></td>
<td>– Billing accuracy of the carrier</td>
</tr>
<tr>
<td></td>
<td></td>
<td>– Equipment availability of the carrier</td>
</tr>
<tr>
<td></td>
<td></td>
<td>– Response of the carrier to unexpected problems</td>
</tr>
</tbody>
</table>
Carrier reputation and carrier evaluation by shippers are correlated, as expected (see Figure 4.13). 70% of carriers responded the same level for both attributes while 30% responded the closest level (e.g. level 4 and 5 or level 5 and 6). Carrier reputation and carrier evaluation by shippers are correlated but they are different concepts. Reputation can be achieved by a good performance in shipments contracts, resulting in a good evaluation by shippers, but also by an efficient marketing strategy (e.g. advertising) implemented by carriers. The current FREMIS formulation assumes that reputation is a function only of carriers’ evaluations by shippers but it can be adapted to incorporate the impact of diverse actions (e.g. advertising) in the improvement of carrier’s reputation in the market.
Figure 4.13: Carrier Evaluation of Their General Evaluation and Reputation (Question Q3C)

Of the attributes that may have an intrinsic relationship with characteristics of the transportation system, delivery reliability and loss/damage are more homogeneous than driver’s quality rating based on survey data (see Figure 4.14, Figure 4.15 and Figure 4.16, respectively).
Figure 4.14: Carrier Evaluation of Their Delivery Reliability (Question Q3C)

Figure 4.15: Carrier Evaluation of Their Loss/Damage of Products (Question Q3C)
Following Friesz and Holguín-Veras (2005), FREMIS is formulated assuming that urban freight markets are not in a stable equilibrium because the market has product differentiation. As a consequence, carrier’s price strategy may not follow the average price in the market. This information was collected in the survey with GTHA freight agents and 47% of carriers claim to adopt a price strategy similar (± 5%) to the average market price, while 26% set their prices below and 28% above the average price (see Figure 4.17). The distribution for price strategy approximately follows a normal distribution (μ = 0%; σ = 8.69%).

Figure 4.16: Carrier Evaluation of Their Drivers Quality (Question Q3C)
An ordered logit is used to identify if price strategy is correlated with carrier attributes and the weight of this correlation. This model can also be used during FREMIS calibration and validation for GTHA market.

Price strategies were grouped into three classes:
- Class 3 (Carrier Price Strategy ≥ +5%): carrier’s price strategy is 5% or more above average price in the market which we expect to be associated with higher level of service
- Class 2 (− 5% ≤ Carrier Price Strategy ≤ 5%): carrier’s price strategy is ± 5% of the average price in the market
- Class 1 (Carrier Price Strategy ≤ − 5%): carrier’s price strategy is 5% or more below average price in the market which we expect to be associated with lower level of service

Using an ordered logit model specification, the probability that a carrier adopts a certain price strategy can be estimated using the following expressions (best model using the available data):

\[ V_{PriceStrat} = \theta_{CarRep7}CarRep7 + \theta_{QualDriv}QualDriv6 + \theta_{QualDriv}QualDriv7 \]  
[4.1]

\[ P(Class 3) = P(Price Strategy ≥ +5%) = \frac{1}{1 + e^{k_{12}V_{PriceStrat}}} \]  
[4.2]
\[ P(\text{Class } 2) = P(-5\% \leq \text{Price Strategy} \leq +5\%) = \frac{e^{k_{32} - V_{\text{PrStrat}}}}{1 + e^{k_{32} - V_{\text{PrStrat}}} - \frac{e^{k_{21} - V_{\text{PrStrat}}}}{1 + e^{k_{21} - V_{\text{PrStrat}}}} \] (4.3)

\[ P(\text{Class } 1) = P(\text{Price Strategy} \leq -5\%) = \frac{e^{k_{21} - V_{\text{PrStrat}}}}{1 + e^{k_{21} - V_{\text{PrStrat}}} \] (4.4)

where:

- \( \text{CarRep7} \): Reputation of the carrier in the market – Level 7 (Exceptional);
- \( \text{QualDriv6} \): Quality of the drivers of the carrier – Level 6 (Excellent);
- \( \text{QualDriv7} \): Quality of the drivers of the carrier – Level 7 (Exceptional);
- \( k_{32} \): threshold parameter in the ordered logit model between class 3 and 2
- \( k_{21} \): threshold parameter in the ordered logit model between class 2 and 1

The results of this estimation are presented below in Table 4.6. All parameters are significant and they have the expected sign. Even though the sample size is small, the \( \rho^2 \) is acceptable and we can observe that carriers influence their price strategy in the market based on their reputation (market aspect) and quality of their drivers (operational aspect).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Std.Error</th>
<th>t-value</th>
<th>Exp.Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta_{\text{CarRep7}} )</td>
<td>1.1643</td>
<td>0.5763</td>
<td>2.020</td>
<td>POS</td>
</tr>
<tr>
<td>( \theta_{\text{QualDriv6}} )</td>
<td>4.8242</td>
<td>1.2058</td>
<td>4.001</td>
<td>POS</td>
</tr>
<tr>
<td>( \theta_{\text{QualDriv7}} )</td>
<td>0.9594</td>
<td>0.5770</td>
<td>1.663</td>
<td>POS</td>
</tr>
<tr>
<td>( k_{21} )</td>
<td>0.0188</td>
<td>0.4032</td>
<td>0.0467</td>
<td></td>
</tr>
<tr>
<td>( k_{32} )</td>
<td>2.8217</td>
<td>0.5856</td>
<td>4.8186</td>
<td></td>
</tr>
</tbody>
</table>

\[ L(0) = -72.50841 \]
\[ L(b) = -55.33041 \]
\[ \rho^2 = 0.2369 \]
\[ n = 66 \text{ carriers} \]

Table 4.6: Carrier Pricing Strategy Model: Results

More research is needed to identify carriers’ price strategy based on their attributes and their condition in the market (e.g. market share, profit margin). The FREMIS formulation presented in this thesis (see Chapter 3) is based on the assumption that carriers can identify the output of their interactions in the market by including terms in the pricing function related to the probability of winning a contract, see Equations (3.11) and (3.14). This approach permits a dynamic representation of carriers’ behaviour, while interacting in the market.
The remaining four attributes collected in the survey (other attributes in Table 4.5) should not be included in FREMIS implementation initially, since they are probably not related to changes in the transportation system. Descriptive statistics of these carrier attributes from survey data are presented in the Appendix 1.

4.2.7. GTHA Freight Rate Model

The last survey result presented in this chapter is a freight rate model based only on weight and distance. The objective of this model is to provide some initial estimates for freight rates charged by companies in the GTHA.

Questions 2C (Q2C) and 2S (Q2S) were used to collect information about one shipment of companies represented on the survey and one part of this question asked information of the usual price charged by a carrier for the shipment (see questions layout on Figure 4.18 and Figure 4.19).

Figure 4.18: Screenshot Carriers’ Survey (Q2C): Shipment Information
The formulation adopted for this model is a translog formulation, which is often interpreted as a second-order approximation to an unknown function form (Greene, 2003). Since this is a freight rate model \( (r_i) \), the independent variable is the price \( (p_i) \) charged for a shipment \( i \) divided by the product of the weight \( (w_i) \) and road distance \( (D_i) \) of the shipment (estimated using a R script embedding Google Maps shortest distance engine). The dependent variables are the weight and road distance of the shipment. The final formulation is presented following. The results of this model using survey data are presented in Table 4.6.

\[
\begin{align*}
    r_i &= \frac{p_i}{w_i d_i} \\
    \ln(r_i) &= \alpha_0 + \alpha_D D_i + \alpha_w w_i + \alpha_{Dw} \ln(D_i) \ln(w_i) + \epsilon_i
\end{align*}
\]
Table 4.7: GTHA Freight Rate Model: Results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Std.Error</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_0$</td>
<td>2.25446</td>
<td>0.56777</td>
<td>3.971</td>
</tr>
<tr>
<td>$\alpha_D$</td>
<td>-0.82061</td>
<td>0.08250</td>
<td>-9.946</td>
</tr>
<tr>
<td>$\alpha_w$</td>
<td>-0.95695</td>
<td>0.10277</td>
<td>-9.311</td>
</tr>
<tr>
<td>$\alpha_{Dw}$</td>
<td>0.04663</td>
<td>0.01421</td>
<td>3.281</td>
</tr>
</tbody>
</table>

$R^2 = 0.9137$  Adj $R^2 = 0.9117$  F-stat = 455.1 on 3 and 129 DF

N = 133, 70 carriers and 63 shippers

The results obtained with this model are more accurate than initially expected ($R^2 = 0.91$) and the regression was able to predict satisfactorily the rates in the survey (see Figure 4.20). Freight rates models are very complex to predict since they are influenced by many shipment characteristics beside distance and weight (e.g. type of commodity). One possible explanation for this accuracy is the existence of freight rate benchmarks followed by agents (e.g. in magazines), which follow a certain functional form and that respondents answered Q2C and Q2S using these references. Another possible explanation is the the homogeneity of shipments in the sample. These aspects are the subject of future research (see Chapter 7).
Using these models, freight price values can be used in a FREMIS implementation for calibration/validation of the models. See, for instance, a contour of freight price values given weight (kg) and distance (km) in Figure 4.21.
4.3. Concluding Remarks

According to the few studies that have been implemented to estimate freight movements in the GTHA region, tour-based movements may represent the greater proportion of freight movements in GTHA region (MITL, 2010). This characteristic supports the application of FREMIS for this freight market.

A self-respondent web survey was designed to obtain parameter values for FREMIS demand models and some information about freight rates in the GTHA freight market. Other parameters in GTHA FREMIS implementation should be either obtained from secondary sources or calibrated using secondary sources. The survey was conducted with shippers and carriers located in GTHA region and resulted in a response rate per type of respondent (manufacturer, wholesaler or motor freight carrier) from 7.7% to 13.8%, which is not uncommon in web surveys with freight companies (Patterson et al, 2010). The demand models are presented in the following chapters.
Other results were presented in this chapter such as a preliminary analysis of freight rates in the market. A strong relationship between carrier prices and attributes was identified for three carrier attributes (carrier reputation, quality of drivers and delivery reliability) using a small sample of carriers (sixty six) who answered this survey question. Another result from this sample is the concentration of carrier price strategies close to the average price in the market, 47% of carriers have a price strategy within 5% of average price. However, 37% of respondents have a price strategy that is more than 10% different than average price, which may indicate that GTHA freight market is not in competitive equilibrium.

Using responses from shipper and carrier surveys, a freight rate model was developed using a translog formulation, a second-order approximation to an unknown function using Taylor series. The goodness-of-fit of the model was good ($R^2 = 0.91$). However, since freight rates are influenced by some variables that were not included on this model (e.g. type of commodity, type of company), this model is the subject of future research (see Chapter 7).
Chapter 5

GTHA Freight Market: Shipment

Bundling Model

Based on the FREMIS formulation (see Chapter 3), this model is used to bundle shipments so as to form shipment contracts. Bundling of shipments is a problem whose complexity increases rapidly with the number of shipments. Therefore, a complete probabilistic model estimated using a web survey to represent this complex process is infeasible to be implemented.

In spite of this, an approach to bundle shipments in FREMIS is proposed in this chapter combining a probabilistic model reflecting dynamics of the market (location of freight movements concentration) and a normative model representing a traditional vehicle routing algorithm (Clarke-Wright algorithm). This chapter presents the parameters of a probabilistic model reflecting dynamics of the market estimated using data collected in the customized web survey (see Chapter 4). The application of the complete shipment bundling model is a subject of future research.

5.1. Bundling of Shipments

Bundling of shipments is a process implemented by agents in freight markets to increase their productivity. Shippers seek a lower price and carriers seek a lower operational cost for the delivery of their shipments. With this approach, agents expect to maximize their profit.

The lower operational cost obtained with bundling shipments can be classified as an economy of scope or scale (Button, 1993). Economies of scope are present in a services market if the provision of a service would reduce the average cost of providing an additional service. It is
similar to economy of scale, but it has a different nature. Economies of scale occur when the average cost is reduced for the same service and economies of scope occur for different services. Therefore, if shipments have very similar characteristics (e.g. origin, destination, type of commodity and required level of service) bundling them is classified as economy of scale rather than economies of scope.

Economies of scope also happen in passenger transportation markets resulting in hub-spoke networks. For instance, deregulation of airline services permitted airline companies to identify the economies of serving one route if another route is also provided (Viscusi et al., 2000). Aguirregabiria and Ho (2012) analysed the US airline market estimating the parameters of a dynamic game of network competition and obtained the empirical support for the importance of economies of scope on this market. Their final conclusion was (Aguirregabiria and Ho, 2012, p. 156): “the most important factor to explain the adoption of hub-and-spoke networks is that the sunk cost of entry in a route declines importantly with the number of cities that the airline connects from the origin and destination airports of the route”. The possibility of economies of scope was also identified in other intercity passenger markets (Meyer and Schmalensee, 1987) and it was one of the motivations for the deregulation of these markets in the 1970s and 1980s (Viscusi et al., 2000). In urban transportation markets, economies of scope are likely more difficult to identify mainly because congestion and interaction with land-use generate more complexities in operational costs.

The existence of these economies in freight markets has been identified for quite some time. Economies of scope/scale are the main motivation of vehicle routing algorithms (Doyuran and Çatay, 2011; Toth and Vigo, 2001), such as the Clarke-Wright or sweeping algorithms. A consequence of the existence of these economies in the freight market is the increasing application of combinatorial auctions in freight transactions (Caplice, 1996; Song and Regan, 2003; Harrison et al., 2004; Sheffi, 2004). In a combinatorial auction, bidders (i.e. carriers) can bid on a specific object (i.e. the delivery of a shipment) or a set of objects (shipments). There is an extensive literature with alternative solutions for two complex problems in combinatorial auctions (see de Vries and Vohra, 2003; Lee et al., 2007; Chang, 2009): bid expression and winner determination problem.
These normative solutions are options for use in FREMIS. However, three reasons justify the adoption of probabilistic (discrete choice) models using agents’ preference data from the market in the FREMIS formulation:

i) Normative algorithms are usually based on deterministic formulations that optimize an agent’s behaviour. This is not recommended in an agent-based model (Law, 2007) since an agent’s behaviour is inherently random in freight markets (Ben-Akiva and Lerman, 1985; Anderson et al., 1992)

ii) Some normative formulations are developed based on equilibrium assumptions (e.g. Freight Network Equilibrium Model developed by Friesz et al., 1985) which may not be valid for the freight market under study

iii) Some normative algorithms are complex to implement and may require a high amount of computing time

Consequently, it is expected that the application of agent’s behavioural model will result in lower computational complexity and more realistic models. Liedtke and Schepperle (2004) came to a similar conclusion and proposed that the freight models should concentrate more on agent’s behaviour rather than on solving complex combinatorial problems.

The procedure proposed for FREMIS in this chapter uses a combination of an ordered logit model, estimated using data from the customized web survey (see Chapter 4), adapted inside a Clarke-Wright algorithm where the savings are substituted by the probability of combining shipments from the ordered logit model. This procedure is detailed in the next section.

5.2. Probabilistic Model: Specification and Results

The input to this procedure is a list of shipments. Each shipment must have at least an origin and a destination. With this information, distance between shipments and some location with a concentration of freight movement (e.g. Toronto, Pearson Airport) are calculated. Distance information is used as an input in the model. The ideal output of a shipment bundling model is the probability of bundling a set of shipments.
The bundling process is based on the relationship between price of delivering a bundle with $n$ shipments, $p(s_1 \cap s_2 \cap ... \cap s_n)$, and the sum of prices of delivering $n$ shipments individually, $p(s_1) + p(s_2) + ... + p(s_n)$. Using this relationship, a set of shipments can be classified in three ways:

- **Complementary:** $p(s_1 \cap s_2 \cap ... \cap s_n) < p(s_1) + p(s_2) + ... + p(s_n) \rightarrow$ combine shipments
- **Substitute:** $p(s_1 \cap s_2 \cap ... \cap s_n) > p(s_1) + p(s_2) + ... + p(s_n) \rightarrow$ do not combine shipments
- **Additive:** $p(s_1 \cap s_2 \cap ... \cap s_n) = p(s_1) + p(s_2) + ... + p(s_n) \rightarrow$ indifferent

There is one important aspect that is not captured if only the distances between locations of shipments are considered in the bundling model. The freight market may have some locations at which a higher concentration of freight is produced or attracted. Examples include freight-hubs (e.g. seaport, intermodal terminals) or downtown areas. These locations and freight-hubs are defined as freight-poles in this model. Since freight-poles concentrate freight movements, if a set of shipments have locations close to this pole, it will be more likely to find other shipments that would permit the combination of shipments.

For instance, suppose that a trucking company is using one vehicle to deliver three shipments between locations 1, 2, 3 and 4 (see Figure 5.1). In Figure 5.1 a), the freight pole is located far from these shipments. As a consequence, the trucking company was not able to find shipments to connect locations 4 and 1 and they had to perform an empty trip (truck without any load). In Figure 5.1 b), the freight pole is located close to these shipments and the trucking was able to find two shipments, which are located at the freight pole, to connect locations 4 and 1.

![Figure 5.1: Freight Pole Example](image-url)
Therefore, in a bundling model distances between shipments and freight-poles should be considered, because agents’ (shippers and carriers) individual perception of the dynamics of the market can be incorporated. As a consequence, explanatory variables that should be adopted in a shipment bundling model must contain, at minimum, the information related to locations of shipments and of freight poles in a region.

A complete probabilistic shipment bundling model is likely infeasible to be estimated or to have data available for its estimation. The number of possible contracts (combinations of shipments) in a set of $N$ shipments, $B_N$, can be calculated using the recursion formula presented in Equation (5.1) (Rota, 1964). This value is called Bell Number and it grows rapidly ($N = 10$, $B_{10} > 10^5$), which imposes a complex challenge in the specification of this model.

$$B_N = \sum_{k=0}^{N-1} \binom{N-1}{k} B_k$$

(5.1)

Since this problem is similar to a vehicle routing problem, this dissertation proposes an approach using two steps:

1) An ordered logit model to estimate the probability of bundling a pair of shipments using parameters estimated from a SP survey
2) A Clarke-Wright algorithm using probabilities developed in the first step, instead of cost savings, to form the set of shipments

Thus, this procedure combines a heuristic of vehicle routing, which is commonly used in commercial packages (Toth and Vigo, 2001), with a probabilistic component that represents the perception of the dynamics in the freight market under study.

To collect data for the ordered logit model, a question was included in the customized web survey (Q2, see Figure 5.2) that asked how often a shipper would combine two similar shipments with different origins/destinations to reduce the price of delivery. Thirteen cities/metropolitan regions were selected to represent both types of freight movement in the GTHA freight market (internal and internal-external movements), see Figure 5.3 and Table 5.1, and seven pairs of shipments were randomly generated from all possible combinations. These seven pairs of shipments were presented to each respondent with distances between shipments.
locations. All distances used in the survey and in this model were calculated using a script in the statistical software R, developed during this research, which embeds Google Directions API\(^1\). This approach calculates distances uniformly and also simplifies the inclusion of freight poles in the model.

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\(^1\) https://developers.google.com/maps/documentation/directions/.

---

**Figure 5.2: Bundling Model of Shipments: Screenshot of Survey Question (Q2)**
Figure 5.3: Cities/Metropolitan Regions GTHA: Bundling Model

Table 5.1: Shipment Bundling Model – Distance Matrix (in km)

<table>
<thead>
<tr>
<th></th>
<th>Toronto, ON</th>
<th>Mississauga, ON</th>
<th>Hamilton, ON</th>
<th>Oshawa, ON</th>
<th>Ottawa, ON</th>
<th>Montreal, QC</th>
<th>Kitchener – Waterloo, ON</th>
<th>Sarnia, ON</th>
<th>Sudbury, ON</th>
<th>Kingston, ON</th>
<th>Detroit, MI</th>
<th>New York, NY</th>
<th>Cleveland, OH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mississauga, ON</td>
<td>30</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hamilton, ON</td>
<td>70</td>
<td>45</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oshawa, ON</td>
<td>60</td>
<td>85</td>
<td>130</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ottawa, ON</td>
<td>450</td>
<td>470</td>
<td>520</td>
<td>390</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Montreal, QC</td>
<td>550</td>
<td>565</td>
<td>610</td>
<td>485</td>
<td>200</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kitchener – Waterloo, ON</td>
<td>105</td>
<td>85</td>
<td>65</td>
<td>150</td>
<td>540</td>
<td>635</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sarnia, ON</td>
<td>290</td>
<td>260</td>
<td>220</td>
<td>335</td>
<td>720</td>
<td>815</td>
<td>200</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sudbury, ON</td>
<td>385</td>
<td>395</td>
<td>440</td>
<td>430</td>
<td>485</td>
<td>685</td>
<td>460</td>
<td>640</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kingston, ON</td>
<td>260</td>
<td>285</td>
<td>330</td>
<td>200</td>
<td>195</td>
<td>290</td>
<td>350</td>
<td>534</td>
<td>630</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Detroit, MI</td>
<td>390</td>
<td>370</td>
<td>330</td>
<td>440</td>
<td>830</td>
<td>920</td>
<td>310</td>
<td>110</td>
<td>745</td>
<td>640</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>New York, NY</td>
<td>765</td>
<td>740</td>
<td>720</td>
<td>805</td>
<td>710</td>
<td>595</td>
<td>775</td>
<td>935</td>
<td>1135</td>
<td>605</td>
<td>990</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cleveland, OH</td>
<td>475</td>
<td>450</td>
<td>430</td>
<td>535</td>
<td>835</td>
<td>930</td>
<td>485</td>
<td>380</td>
<td>840</td>
<td>735</td>
<td>275</td>
<td>745</td>
<td></td>
</tr>
</tbody>
</table>
The characteristics of each shipment (e.g. weight, value) used information from questions Q2S and Q2C to improve the realism of the experiment. The characteristics of the second shipment were the same as the first shipment. Respondents were asked how often they thought these combinations would be bundled in one contract to reduce the freight rate, using a Likert 7-scale from “never” to “always” with the odds given as percentages, e.g. “Frequently (80-99%)”.

An approach was developed using distances between shipments and freight-poles (see Figure 5.4) to incorporate these elements into the probabilistic model. Six distances were calculated:

1) Distance between shipments ($d_{12}$ and $d_{21}$), which can be used to calculate the dead-heading distance (distance a truck operates without cargo) for the pair of shipments.

2) Distances to each freight-pole (locations with a concentration of freight flows), $d_{FP,O1}$, $d_{FP,O2}$, $d_{FP,D1}$ and $d_{FP,D2}$ and the minimum distance between shipment locations (origin and destination) and the freight pole were selected as explanatory variables.

---

2 It is assumed that is more likely for a carrier to pickup and delivers a shipment before picking up a second shipment. This assumption is also adopted in vehicle routing algorithms with pickup and delivery (Toth and Vigo, 2001)
Two freight-poles in the GTHA were included in the probabilistic model: City of Toronto and Pearson International Airport. The assumption is that these locations would have a high concentration of shipments either originating or destined there. The exact location of these poles in Google Maps is presented in Figure 5.5 and Figure 5.6. The minimum distance between each freight-pole and shipment locations was included as an explanatory variable to represent the minimum distance to pickup or delivery a shipment with location at the freight-pole. Therefore, this variable represents the weight of the location of a freight pole in concentrating shipments. Another explanatory variable with the value of $d_{12} + d_{21}$ was included to represent the dead-heading distance. This variable represents the average dead-heading distance of a pair of shipment since the order of delivery of shipments is undefined. To capture both side of the perception about the freight market in the region, the survey was conducted with shippers and carriers. A dummy variable was included in the specification to represent if the respondent is a carrier or not.
Figure 5.5: Toronto Location Google Maps: Nathan Philips Square

Figure 5.6: Pearson International Airport Location in Google Maps: Terminal 1
The specification adopted is an ordered logit model with seven classes:

- Class 7: Always (100%)
- Class 6: Frequently (80 to 99%)
- Class 5: Often (60 to 79%)
- Class 4: Sometimes (40 to 59%)
- Class 3: Seldom (20 to 39%)
- Class 2: Almost never (1 to 19%)
- Class 1: Never (0%).

The probability of respondent choosing one of these categories is considered to be a function of $V$:

$$V_{SHIPMENTS\ i,j} = \beta_{DeadHeadDist\ i,j} DeadHeadDist_{i,j} + \beta_{LogMinDist\ Tor\ i,j} LogMinDistTor_{i,j} + \beta_{LogMinDist\ Carrier Airp\ i,j} LogMinDistAirp_{i,j} + \beta_{Carrier\ Shipper\ i,j} Carrier$$

(5.2)

where:

$$DeadHeadDist_{i,j} = d_{i2} + d_{21}$$

(5.3)

$$LogMinDistTor_{i,j} = \log[\min(d_{TOR\ O1}, d_{TOR\ D1}, d_{TOR\ O2}, d_{TOR\ D2}) + 1]$$

(5.4)

$$LogMinDistAirp_{i,j} = \log[\min(d_{AIR\ O1}, d_{AIR\ D1}, d_{AIR\ O2}, d_{AIR\ D2}) + 1]$$

(5.5)

$$Carrier = \begin{cases} 
1, & \text{respondent is a carrier} \\
0, & \text{respondent is a shipper} 
\end{cases}$$

(5.6)

Using Equations (5.2) to (5.6), the probability of a respondent choosing one of the seven categories is estimated using the following expressions (Train, 2009):

$$P[\text{Always (100%)}] = P[C7] = \frac{1}{1 + \exp[\mu_B (k_{67} - V)]}$$

(5.7)

$$P[\text{Frequently (80 to 99%)}] = P[C6] = \frac{\exp[\mu_B (k_{67} - V)] - \exp[\mu_B (k_{56} - V)]}{1 + \exp[\mu_B (k_{67} - V)] - \exp[\mu_B (k_{56} - V)]}$$

(5.8)

$$P[\text{Often (60 to 79%)}] = P[C5] = \frac{\exp[\mu_B (k_{56} - V)] - \exp[\mu_B (k_{45} - V)]}{1 + \exp[\mu_B (k_{56} - V)] - \exp[\mu_B (k_{45} - V)]}$$

(5.9)

$$P[\text{Sometimes (40 to 59%)}] = P[C4] = \frac{\exp[\mu_B (k_{45} - V)] - \exp[\mu_B (k_{34} - V)]}{1 + \exp[\mu_B (k_{45} - V)] - \exp[\mu_B (k_{34} - V)]}$$

(5.10)

$$P[\text{Seldom (20 to 39%)}] = P[C3] = \frac{\exp[\mu_B (k_{34} - V)] - \exp[\mu_B (k_{23} - V)]}{1 + \exp[\mu_B (k_{34} - V)] - \exp[\mu_B (k_{23} - V)]}$$

(5.11)
\[
P[\text{Almost never (1 to 19\%)}] = P[C2] = \frac{\exp[\mu_B(k_{23} - V)] - \exp[\mu_B(k_{12} - V)]}{1 + \exp[\mu_B(k_{23} - V)] - 1 + \exp[\mu_B(k_{12} - V)]} \tag{5.12}
\]
\[
P[\text{Never (0\%)}] = P[C1] = \frac{\exp[\mu_B(k_{12} - V)]}{1 + \exp[\mu_B(k_{12} - V)]} \tag{5.13}
\]

where:
- \(k_{12}\): threshold parameter in the ordered logit model between class 1 and 2
- \(k_{23}\): threshold parameter in the ordered logit model between class 2 and 3
- \(k_{34}\): threshold parameter in the ordered logit model between class 3 and 4
- \(k_{45}\): threshold parameter in the ordered logit model between class 4 and 5
- \(k_{56}\): threshold parameter in the ordered logit model between class 5 and 6
- \(k_{67}\): threshold parameter in the ordered logit model between class 6 and 7
- \(\mu_B\): scale parameter of Gumbel distribution (normalized to 1 to permit identification of the model).

The results of the estimation are presented in Table 5.2. Model specifications were estimated and it was identified that the log of the distance to freight-poles resulted in better estimates.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>St. Error</th>
<th>Z value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta_{\text{DeadHeadDist}})</td>
<td>-0.001647</td>
<td>0.0003305</td>
<td>-4.984</td>
</tr>
<tr>
<td>(\beta_{\text{LogMinDistFor}})</td>
<td>-0.042262</td>
<td>0.0413384</td>
<td>-1.022</td>
</tr>
<tr>
<td>(\beta_{\text{LogMinDistAirp}})</td>
<td>-0.349706</td>
<td>0.1156569</td>
<td>-3.024</td>
</tr>
<tr>
<td>(\beta_{\text{Carrier}})</td>
<td>-0.452883</td>
<td>0.1782475</td>
<td>-2.541</td>
</tr>
<tr>
<td>(k_{12})</td>
<td>-3.0345</td>
<td>0.4922</td>
<td>-6.1656</td>
</tr>
<tr>
<td>(k_{23})</td>
<td>-2.3628</td>
<td>0.4842</td>
<td>-4.8802</td>
</tr>
<tr>
<td>(k_{34})</td>
<td>-1.8581</td>
<td>0.4809</td>
<td>-3.8641</td>
</tr>
<tr>
<td>(k_{45})</td>
<td>-1.2316</td>
<td>0.4792</td>
<td>-2.5700</td>
</tr>
<tr>
<td>(k_{56})</td>
<td>-0.8722</td>
<td>0.4794</td>
<td>-1.8192</td>
</tr>
<tr>
<td>(k_{67})</td>
<td>-0.4428</td>
<td>0.4816</td>
<td>-0.9193</td>
</tr>
</tbody>
</table>

\[
L(0) = -842.579 \quad L(\beta) = -740.431 \quad -2\times(L(\beta)-L(0))= \quad \rho^2 = 0.1212
\]

\(N = 433\) responses \quad Sample: 43 carriers and 47 shippers
It is observed that all the signs are as expected and most of the \( k \) values, cut-off variables, are significant with the exception of the \( k \) that divides classes 6 and 7 \( (k_{67}) \). One possible explanation for the latter result is the high values of the dead-heading variable in the database (see Figure 5.7). Since less than 6\% of the observations had the dead-heading distance lower than 50km, alternative “Always” may have become a dominated alternative in the experiment.

![Figure 5.7: Dead Head Variable: Sample Distribution](image)

The approach adopted in the survey has this shortcoming. Although both types of GTHA freight movements are represented in the survey (Internal and Internal-External), the random selection of shipment combinations with internal and external locations increases the occurrence of high values of the dead-heading variable. This reduces the probability of combining these shipments, consequently reducing the significance of \( k_{67} \) estimates. Therefore, another survey should be implemented to estimate this model using only GTHA locations.

The distributions of the other distance variables in the model are presented in Figure 5.8 and Figure 5.9. Shipments with locations close to the City of Toronto increase their likelihood of being bundled (negative sign of the parameter), however the estimated value was not significant. Differently to this, the parameter for the minimum distance to Pearson Airport is significant and
the absolute value of this parameter is more than 8 times higher than city of Toronto distance parameter. This result represents the higher impact on bundling decisions for shipments located close to the Pearson Airport, where most freight movements in GTHA region are likely concentrated.

Figure 5.8: Minimum Distance to Toronto Location: Sample Distribution

Figure 5.9: Minimum Distance to Pearson Airport Location: Sample Distribution
5.3. Concluding Remarks

A simplified approach is proposed for FREMIS GTHA implementation, which combines a model to predict the probability of bundling two shipments in the freight market and traditional vehicle routing algorithms (e.g. Clarke-Wright). The results show that dead-head distance, the distance during which a vehicle is traveling without generating revenue for its owner, and the distance to freight poles, locations with a high concentration of freight movements, were relevant in this model.

Bundling of shipments is a complex process because it involves a number of possible combinations that increases rapidly with the number of shipments. A SP web survey to capture agent behaviour in this process would probably require some advanced methods of survey design (e.g. qualitative surveys, advance web programming methods) that were not included on this research project.
Chapter 6

GTHA Freight Market: Carrier Selection Model

This chapter presents the results of the second demand model for GTHA freight market simulation using data from the customized web-survey presented in Section 4.2. In the market simulation proposed in FREMIS, shippers have to select carriers for the provision of logistics services in the contracts formed by bundling shipments (first demand model). These contracts are named Logistics Services Contracts in Roorda et al. (2010). Data for this second model are collected using a stated preference (SP) survey embedded in the customized web-survey.

The first part of this chapter presents a review of carrier selection with a focus on which carrier attributes are included in this process. This review is mainly based on Meixell and Norbis (2008). The focus is on studies conducted in North America and used to identify the most relevant motor freight carrier attributes. These attributes were included in the SP survey. Only studies implemented after 1980s freight deregulation were included. Since freight deregulation had a direct impact on market dynamics with an increase on competition, the carrier selection process may have led to a focus on different carrier attributes. The result of this review is the selection of a set of attributes to be used in the SP experiment.

The second part of this chapter describes the experiment design implemented for the SP question in the customized web-survey. The final objective of a SP survey design is to provide data for accurate models. Two aspects were considered in this SP design to increase model accuracy. First, the survey asked respondents to rate the importance of attributes for carrier selection and included only top rated attributes in the SP survey. This procedure aims to
minimize the non-attendance problem. Second, the set of designs are D-efficient designs, which have the objective of minimizing the generalized variance of the parameter estimates.

The third and final part of this chapter presents the results of three carrier selection models developed for GTHA freight market simulation. These models are distinguished by the analysis of two errors that may influence their accuracy, the non-response bias and the non-attendance problem. The non-response bias occurs when the results of models developed from survey respondents and nonrespondents are different between them (Bethlehem et al., 2011). The non-attendance problem occurs when a respondent does not consider all alternative attributes during the decision process in a choice experiment (Hensher and Greene, 2010).

The first model is a selection model without the analysis of these two errors. The second model adjusts for nonresponse bias using a weighting adjustment for the observations. The third model accounts for both errors. All three models assume that respondents are heterogeneous, which is represented by a function for the Gumbel distribution scale (or variance) based on respondent characteristics (sales volume). As a result, these models assume that there is heteroscedasticity (different variance) in the response process.

### 6.1. Carrier Selection: Attributes

The attributes considered by shippers in carriers’ selection processes have been analysed by several studies. Traditionally, these studies focused on determining the relative importance of selection criteria using literature reviews or surveys with either shippers or carriers or both. Meixell and Norbis (2008) present an extensive review of the carrier selection literature. They analysed peer-reviewed journal papers (from 1988 to 2008) and practitioner articles. The main references cited on this review are analysed and presented next.

One of the first studies after freight deregulation is presented by McGinnis (1990). McGinnis (1990) reviews literature pertaining to the importance of service related attributes and cost in transportation choice before and after deregulation. Factors that were identified as relevant in most of the studies included freight rate, reliability, and carrier considerations (e.g. reputation). Furthermore, service variables were found to be more important than freight rate on average.
Most of the studies in literature have used surveys to draw their conclusions. One of the first studies, after deregulation, is presented by Foster and Strasser (1991), who conducted a survey with carriers and shippers. They concluded that selection criteria are best viewed as a package, which supports the adoption of utility-based approaches to analyse carrier selection.

Lambert et al. (1993) conducted a survey with shippers to analyse the selection and evaluation of less-than-truckload motor carriers. The rate of importance of 166 carrier attributes in the selection process was collected. Most important attributes (based on mean rate) were related to operations/logistics (e.g. on-time pickups/deliveries, loss and damage claims) and to price (e.g. competitive rates). The least important attributes were associated to marketing strategies (e.g. promotional gifts, direct mail, and advertising). Another important finding of this survey is that “lowest rates” ranked only 40\textsuperscript{th} in importance, while competitive rates were ranked 4\textsuperscript{th}.

Crum and Allen (1997) developed a similar study but used a sample of carriers to identify carriers’ perception of importance in their selection by shippers. Twenty attributes were included and the mean rate of importance was compared to another similar study with carriers conducted in 1990 (Crum and Allen, 1991). The main objective was to compare the impact of the increasing level of outsourcing in supply chains from 1990 to 1996. The set of ten highest ranked attributes is practically the same in both studies however there is an increase in the mean rate of importance from 1990 to 1996 studies. This result is consistent with an increase in quality service by shippers. In the end, the highest ranked carriers’ attributes were similar to Lambert et al. (1993).

Murphy et al. (1997) also collected the rate of importance of carriers’ attributes using a survey, but based on both agents’ perceptions. Besides the rate of importance, they also analysed the difference on mean score and on the rank of attributes between agents. Shippers assigned a higher rate of importance than carriers for almost all of carriers’ attributes. Regarding the rank of attributes, a high degree of similarity was identified between shippers and carriers ranks (0.804 Spearman coefficient of rank correlation). Four of the five highest ranked attributes were the same for both agents and they are similar to Crum and Allen (1997) and Lambert et al. (1993).
In Kent et al. (2001), shippers’ perceptions were evaluated for the importance of carriers’ attributes in five segments of the truckload transportation industry: dry van, temperature controlled, tank, intermodal and flatbed. Significant differences were identified between two segments: dry van and temperature controlled. Eight carriers’ attributes were rated close to the higher rate value in all five segments including the same attributes of previous studies besides some other attributes such as carrier reputation, billing accuracy, equipment availability, quality of drivers and follow-up on service complaints.

The objective of Voss et al. (2006) study was to identify the emphasis shippers place on carriers’ attributes after the terrorist attacks of September 11th, 2001. This study can also be used to identify how shippers change their selection criteria in a recession environment, a consequence of the attacks and the “dot-com bust”. The authors used a model called Theory of Reasoned Action (TRA) to derive the mean rate of importance of carriers’ attributes. The five highest ranked carriers’ attributes were similar to previous studies with the inclusion of the attribute “ability to respond to unforeseen problems”, a consequence of recent terrorist attacks.

One common feature of these studies is that the top ranked carrier attributes have a mean rate similar to each other. The difference on the mean rate of importance between the top ranked and the lowest ranked (8th, 9th or 10th) in the five above references ranges from 0.2 (earliest study) to 1.2 (latest study), see Table 6.1. Therefore, it is difficult to select among the top ranked attributes, which one should be included or not in a carrier selection survey.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Number of Attributes in the rank</th>
<th>Difference (top ranked to last)</th>
<th>Type of Respondent</th>
<th>Scale</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lambert et al. (1993)</td>
<td>10</td>
<td>0.2</td>
<td>Shippers</td>
<td>1 to 7</td>
<td>Mean rate</td>
</tr>
<tr>
<td>Crum and Allen (1997)</td>
<td>10</td>
<td>1.1</td>
<td>Carriers</td>
<td>1 to 7</td>
<td>Mean rate</td>
</tr>
<tr>
<td>Murphy et al. (1997)</td>
<td>10</td>
<td>0.6 (shippers), 0.9 (carriers)</td>
<td>Both</td>
<td>1 to 5</td>
<td>Mean rate</td>
</tr>
<tr>
<td>Kent et al. (2001)</td>
<td>8</td>
<td>0.36 to 0.50 (four industries) and 0.82 (intermodal)</td>
<td>Shippers</td>
<td>1 to 7</td>
<td>Mean rate</td>
</tr>
<tr>
<td>Voss et al. (2006)</td>
<td>9</td>
<td>1.2</td>
<td>Shippers</td>
<td>1 to 5</td>
<td>TRA (regression)</td>
</tr>
</tbody>
</table>

Using these papers, the attributes in the SP survey were selected. First, the quantity of attributes (ten) was defined because of the limit of the number of attributes that should be in a SP survey (seven, see Pearmain and Kroes, 1990) and the small difference among the ten top ranked
attributes in the references (see Table 6.1). Second, ten attributes were selected, which were consistently in the ten top ranked attributes in these references and were considered relevant in FREMIS. The selected ten attributes can be classified into four types:

- Carrier general evaluation/reputation in the market (2 attributes): “General evaluation of the carrier by the shippers” and “Reputation of the carrier in the market”
- Attributes likely related to the transportation system (3 attributes): “Delivery reliability of the carrier”, “Quality of the drivers of the carrier”, “Loss / damage of products during deliveries of the carrier”
- Pricing of the carrier (1 attribute)
- Other attributes (4 attributes): “Follow-up by the carrier on service complaints”, “Billing accuracy of the carrier”, “Equipment availability of the carrier”, “Response of the carrier to unexpected problems”

### 6.2. Stated Preference Survey: Experimental Design

Permain and Kroes (1990) suggest that a maximum of seven attributes should be used in a stated preference (SP) survey. Since ten attributes were selected for this SP survey, a procedure in the survey should be implemented to avoid the non-attendance problem (Hensher and Greene, 2010). The non-attendance problem occurs when an attribute is included in a SP experiment, but is not considered by the respondent in the decision process. The consequence is the reduction of the significance of its parameters. To accomplish this, shippers were asked to provide their rate of importance for each carrier attribute: from “Unimportant” to “Very Important” (see Figure 6.1). Only the attributes that were selected as “Important” or “Very Important” were included in the SP survey question. If this resulted in less than two attributes in the SP design, the SP experiment was skipped and next question in the survey was presented (see Figure 4.10).
This procedure results in a set of different SP designs for each respondent. In total, 1,014 different designs may be presented to a respondent, $2^{10} = 1,024$ designs minus 10 designs with one attribute only. To cover all 1,014 designs, nine different SP designs were developed with all possible numbers of attributes selected by the respondent (from two to ten attributes selected) combined with a list of values for carrier attributes, see Table 6.2. These values were defined based on information collected in magazines and with shippers and carriers. Using the information collected from carriers in Question 3C, values in Table 6.2 can be validated with actual values in GTHA freight market.

### Table 6.2: Carrier Attributes Levels

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Scale</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrier reputation</td>
<td>From 1-Very Poor to 7-Exceptional</td>
<td>3</td>
<td>5</td>
<td>7</td>
</tr>
<tr>
<td>Response to problems</td>
<td>Percentage of unexpected problems solved without impacting the operation</td>
<td>85%</td>
<td>90%</td>
<td>95%</td>
</tr>
<tr>
<td>Quality of drivers</td>
<td>From 1-Very Poor to 7-Exceptional</td>
<td>3</td>
<td>5</td>
<td>7</td>
</tr>
<tr>
<td>Competitive pricing</td>
<td>Compared to the expected price</td>
<td>10% below same 10% above</td>
<td>10% above</td>
<td></td>
</tr>
<tr>
<td>Follow-up on service complaints</td>
<td>Time to give a follow-up</td>
<td>1 day</td>
<td>1 week</td>
<td>1 month</td>
</tr>
<tr>
<td>Billing accuracy</td>
<td>Percentage of bills accurate</td>
<td>85%</td>
<td>90%</td>
<td>95%</td>
</tr>
<tr>
<td>Equipment availability</td>
<td>Percentage with equipments available</td>
<td>85%</td>
<td>90%</td>
<td>95%</td>
</tr>
<tr>
<td>Delivery reliability</td>
<td>Percentage of pickup/delivery on time</td>
<td>85%</td>
<td>90%</td>
<td>95%</td>
</tr>
<tr>
<td>Loss / damage of products</td>
<td>Average lost/damage in shipment value (%)</td>
<td>2%</td>
<td>4%</td>
<td>6%</td>
</tr>
<tr>
<td>Past experience</td>
<td>From 1-Very Poor to 7-Exceptional</td>
<td>3</td>
<td>5</td>
<td>7</td>
</tr>
</tbody>
</table>
The SP-designs were constructed using a D-efficient design procedure in the software SAS, assuming the null hypothesis for the values of the parameters ($\beta_1 = ... = \beta_k = 0$). The SP-designs adopted are presented in Appendix 2. In a D-efficient design, the D-error is minimized, which is given as

$$\text{det} \left[ I(\beta)^{-1} \right]_k$$

This term is the determinant of the inverse of the Fisher Information, $I$, for a design given a particular econometric model form and certain parameter estimates, $\beta$, scaled by one over the number of parameters, $k$ (Hensher and Greene, 2010). The inverse of the Fisher Information matrix is equal to the variance-covariance matrix (Greene, 2003). Therefore, in a D-efficient design the volume of the asymptotic joint confidence sphere surrounding the parameter estimates is minimized (Kanninen, 2002).

With the selection of the attributes that should be included in the SP-experiment (Figure 6.1) and levels of the attributes (Table 6.2), a SP-experiment was customized and presented for each shipper respondent (see the screen of one example of the question in Figure 6.2).

![Figure 6.2: Screenshot SP Experiment: Example](image)

### 6.3. Carrier Selection Models

Three different specifications for GTHA carrier selection model were developed during this research. All models use a multinomial logit structure. Other discrete choice model structures were analysed, such as the nested logit and the multinomial probit, however they do not provide
a significant improvement in the final estimates. Therefore, correlation between alternative utility random terms was not identified during the estimation process and the IIA property holds for the data (Train, 2009).

This result is expected since most of the alternatives presented in the SP survey are unlabelled (Louviere et al., 2000), i.e. their names (labels) are not associated with any utility to the respondent. In usual SP transportation mode choice surveys, alternative are labelled (e.g. subway, bus, and auto) and the IIA property should be tested.

The models presented in this chapter assume that the correlations between decisions of the same respondent can be considered negligible with the representation of heteroskedastic behaviour (different variance) per respondent in the model. As a consequence, the observations from the same respondent are not considered totally independent, which is traditionally assumed in models developed from SP survey. However, some correlation among these observations may still exist and the investigation of these correlations is the subject of future research.

6.3.1. Attributes Selected

The first result is carrier attributes importance level obtained from SP respondents. Based on the literature review presented in Section 6.1, service attributes are expected to be more important than price. The data collected in the survey demonstrated that competitive pricing is the 4th attribute in terms of the mean rating (1 for the lower rate and 5 for the higher), see Figure 6.3, with delivery reliability and loss/damage being considered the most important attributes. 32% of shippers chose all ten attributes as important or very important in carrier selection. Another interesting result of this sample of respondents is the low importance of the attributes related to carrier performance, general experience with shippers and carrier reputation. However, the sample size is small to generalize this type of conclusion.
Most of the respondents (77%) selected more than seven attributes as important or very important, see Figure 6.4. This result may reduce the quality of the final estimates because 68 respondents (77%) have to evaluate more than seven attributes simultaneously, i.e. the non-attendance problem should be analysed. Therefore, a framework was developed to analyse this problem (see Section 6.3.4).
6.3.2. Heteroskedastic Selection Model: No Bias Analysis

The specification of this model is a multinomial logit model with three or four unlabelled alternatives (carriers) and one labelled alternative “None of them”. The utility of alternative “None of them” represents a reservation value a shipper has in each decision. For instance, if carriers included in the SP experiment do not provide a certain utility level, shippers select the alternative “None of them”. The parameters obtained for this function can also be used to validate the hypothetical alternatives included in the experiment. If hypothetical alternatives cover most of the situations that carriers encounter in the market then probability of selecting “None of them” should be low.

The most accurate specification for each carrier systematic utility function is presented in Equations (6.2) and (6.3).

\[
V_{s,c} = \beta_{\text{CarRep5CarRep5}} + \beta_{\text{CarRep5CarRep7}} + \beta_{\text{QualDrvQualDrv7}} + \beta_{\text{FollServFollServ}} + \\
\quad + \beta_{\text{EqAvail85\%EqAvail85\%}} + \beta_{\text{EqAvail85\%EqAvail90\%}} + \beta_{\text{EqAvail85\%EqAvail95\%}} + \\
\quad + \beta_{\text{DelRelDelRel}} + \beta_{\text{LossDamProdLossDamProd}} + \beta_{\text{PricePrice}} + \\
\quad + \beta_{\text{PastExp3PastExp3}} + \beta_{\text{PastExp5PastExp5}} + \beta_{\text{PastExp5PastExp7}} + \beta_{\text{PastExp7PastExp7}}
\] (6.2)
where (see Table 6.2 with the values for these attributes),
- CarRep5: dummy variable, 1 if carrier $c$ reputation rate is 5 and 0 otherwise
- CarRep7: dummy variable, 1 if carrier $c$ reputation rate is 7 and 0 otherwise
- QualDriv7: dummy variable, 1 if carrier $c$ drivers quality is 7 and 0 otherwise
- FollServ: carrier’s time to give a follow-up on service complaints in days
- EqAvail85%: dummy variable, 1 if carrier $c$ equipment is available 85% of the time, and 0 otherwise
- EqAvail90%: dummy variable, 1 if carrier $c$ equipment is available 90% of the time, and 0 otherwise
- EqAvail95%: dummy variable, 1 if carrier $c$ equipment is available 95% of the time, and 0 otherwise
- DelRel: delivery reliability of carrier $c$ in percentage of pickup/delivery on time (values from 0.85 to 0.95)
- LossDamProd: average lost/damage of carrier $c$ in percentage of shipment value (values 0.02 to 0.06)
- Price: factor to represent the price charged by carrier $c$ compared to the average price in the market, equals to one plus percentage of increase/reduction (see also Table 6.2)
- PastExp3: dummy variable, 1 if past experience rate with carrier $c$ is 3 and 0 otherwise
- PastExp5: dummy variable, 1 if past experience rate with carrier $c$ is 5 and 0 otherwise
- PastExp7: dummy variable, 1 if past experience rate with carrier $c$ is 7 and 0 otherwise

The representation of heterogeneity in respondent choice is performed using a function for the scale parameter of the Gumbel distribution for each shipper $s$, $\mu_s$. Some different function shapes were analysed (e.g. exponential, logarithm, linear) and the best results were obtained using the power function presented in Equation (6.4).

$$
\mu_s = \left( \frac{\text{sales}_s}{\text{sales}_{\min}} \right)^{Y_{s\text{adv}e}}
$$

(6.4)
- sales<sub>s</sub>: sales volume of shipper <i>s</i> from 2009 InfoCanada database
- sales<sub>min</sub>: value of the minimum average sales volume in the data ($125,000), required to identify the model

The scale parameter of the Gumbel distribution can be used to calculate the variance of the random terms using Equation (6.5). Substituting Equation (6.4) into (6.5), an expression for the variance of the random terms for each shipper <i>s</i> given the shipper sales volume and parameter γ<sub>ScalePar</sub> is presented in Equation (6.6).

\[
\sigma_s = \frac{\pi}{\mu_s \sqrt{6}} \quad (6.5)
\]

\[
\sigma_s = \frac{\pi}{\sqrt{6}} \left( \frac{\text{sales}_s}{\text{sales}_{\text{min}}} \right)^{-\gamma_{\text{ScalePar}}} \quad (6.6)
\]

Using the value of the scale parameter for each respondent, μ<sub><i>s</i></sub>, the probability of a shipper selecting a carrier can be calculated using Equations (6.7) and (6.8). The scale parameter can be used to represent respondent’s rationality, which is associated with random and deterministic behaviour (Anderson et al., 1992). Respondents with a higher scale have a more rational and deterministic behaviour. For instance, if μ<sub><i>s</i></sub> → 0 then the probability of selecting a carrier tends to (1 / number of carriers), see Equations (6.7) and (6.8). Furthermore, if μ<sub><i>s</i></sub> → ∞ then the probability of selecting a carrier tends to 1 for the carrier with the higher utility and zero for other carriers. The final results of this model are presented in Table 6.3.

\[
P_{s,c} = \frac{\exp(\mu_s V_{s,c})}{\exp(\mu_s V_{s,NONE}) + \sum_c \exp(\mu_s V_{s,c})} \quad (6.7)
\]

\[
P_{s,NONE} = \frac{\exp(\mu_s V_{s,NONE})}{\exp(\mu_s V_{s,NONE}) + \sum_c \exp(\mu_s V_{s,c})} \quad (6.8)
\]
Table 6.3: Heteroskedastic Selection Model: No Bias Analysis

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Value</th>
<th>Std.Error</th>
<th>t value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{\text{CarRep5}}$</td>
<td>0.2035</td>
<td>0.0934</td>
<td>2.1792</td>
</tr>
<tr>
<td>$\beta_{\text{CarRep7}}$</td>
<td>0.2795</td>
<td>0.1071</td>
<td>2.6085</td>
</tr>
<tr>
<td>$\beta_{\text{QualDriv7}}$</td>
<td>0.2220</td>
<td>0.0903</td>
<td>2.4578</td>
</tr>
<tr>
<td>$\beta_{\text{FolServComp}}$</td>
<td>-0.0228</td>
<td>0.0081</td>
<td>-2.7963</td>
</tr>
<tr>
<td>$\beta_{\text{EquipAvail85%}}$</td>
<td>-0.3454</td>
<td>0.1535</td>
<td>-2.2506</td>
</tr>
<tr>
<td>$\beta_{\text{EquipAvail90%}}$</td>
<td>-0.2685</td>
<td>0.1391</td>
<td>-1.9304</td>
</tr>
<tr>
<td>$\beta_{\text{EquipAvail95%}}$</td>
<td>-0.2118</td>
<td>0.1298</td>
<td>-1.6325</td>
</tr>
<tr>
<td>$\beta_{\text{DelRel}}$</td>
<td>0.8071</td>
<td>0.3976</td>
<td>2.0298</td>
</tr>
<tr>
<td>$\beta_{\text{LossDamProd}}$</td>
<td>-9.8537</td>
<td>3.5760</td>
<td>-2.7555</td>
</tr>
<tr>
<td>$\beta_{\text{PastExp3}}$</td>
<td>-0.5463</td>
<td>0.2265</td>
<td>-2.4118</td>
</tr>
<tr>
<td>$\beta_{\text{PastExp5}}$</td>
<td>-0.3253</td>
<td>0.1616</td>
<td>-2.0127</td>
</tr>
<tr>
<td>$\beta_{\text{PastExp7}}$</td>
<td>-0.1415</td>
<td>0.1255</td>
<td>-1.1282</td>
</tr>
<tr>
<td>$\beta_{\text{Price}}$</td>
<td>-1.9764</td>
<td>0.7672</td>
<td>-2.5762</td>
</tr>
<tr>
<td>$\beta_{\text{NoneASC}}$</td>
<td>-1.8638</td>
<td>0.7806</td>
<td>-2.3877</td>
</tr>
<tr>
<td>$\gamma_{\text{ScalePar}}$</td>
<td>0.2384</td>
<td>0.0832</td>
<td>2.8643</td>
</tr>
</tbody>
</table>

$L(0) = -774.689$  \hspace{1cm} $L(\beta) = -664.508$  \hspace{1cm} $\rho^2 = 0.142$

\[ n = 83 \text{ shippers} \hspace{1cm} N = 482 \text{ obs} \hspace{1cm} \text{AIC}^1(\beta) = 1,363.43 \]

Even though the sample size is small, the results are very consistent:

- Carrier reputation has positive parameters for both levels 5 and 7. The parameter for carrier reputation level 3 was not significant. This result demonstrates that shippers assign a significant utility portion on reputation in the market, which is also encountered in the literature (Meixell & Norbis, 2008)

- Quality of drivers is only significant in the maximum rate level (7) but the parameter value is close to carrier reputation

- Follow-up in service complaints parameter is negative and represents shipper’s disutility to long follow-ups

- Equipment availability parameters are all negative and they are approaching zero as the percentage approaches 1. This result may demonstrate that shippers assign a disutility for any carrier who they expect will not provide the equipment required for all of their shipments

\[^1\text{AIC: Akaike Information Criteria.}\]
• The values of the parameters of past experience have a very similar behaviour to equipment availability. They approach zero when the rate of past experience approaches the maximum value (7). Therefore, shippers assign a negative utility if past experience with the carrier is lower than 7
• Delivery reliability and loss and damage both have the expected sign. Besides that, reduction of 1% in loss/damage increase shippers’ utility is more than ten times if compared to an increase of 1% in delivery reliability. Shippers are more sensitive to changes in loss/damage
• The alternative-specific constant (ASC) of alternative “None of them” has a negative value and it represents the low probability that a respondent would select none of the alternatives presented in the SP instrument.

Another interesting result is the value of parameter $\gamma_{\text{ScalePar}}$. It is significantly differently from zero. A value of zero would result in no heterogeneity between shippers. A positive sign for this parameter represents that the scale of the random terms are increasing with sales volume. Therefore, based only on the data collected in the SP experiment, bigger companies (higher sales volume) would have a more deterministic behaviour in the carrier selection process than smaller companies, see Figure 6.5, i.e. the weight of observed carrier attributes would be higher.
One major problem in self-respondent surveys is non-response (or selectivity) bias. This bias exists when respondents and non-respondents have different responses for the same questions in the survey (Bethlehem et al., 2011). A well-known procedure for regression models to correct the nonresponse bias is the Heckman correction (Greene, 2003). However, this correction only applies for linear models. Few references analyse remedies for this bias in the discrete model case (Dubin and Rivers, 1989) and they use multivariate models (e.g. probit) to jointly model the discrete responses in the survey with a model for the probability of responding.

Joint modelling of SP responses with probability of responding was considered during this research to identify nonresponse bias. However the data are too unbalanced for a joint estimation because a high number of companies were not selected during the recruitment phase (not participants of GTHA freight market) or did not started to respond the survey. Figure 6.6 summarizes this process using a classification adapted from Bethlehem et al. (2011). Companies
in the sample were classified in seven outcomes (see circles and their classification in Figure 6.6).

i) Outcome 1: companies not successfully contacted during the recruitment phase

ii) Outcome 2: companies contacted but not eligible to participate in the survey (not active in the freight market)

iii) Outcome 3: companies contacted and eligible to participate but did not start the survey

iv) Outcome 4: companies which are carriers in the freight market and not eligible to participate in the SP experiment

v) Outcome 5: shippers that select carriers using only price as a criterion

vi) Outcome 6: shippers that select carriers using price and other attributes which were not able to answer SP survey

vii) Outcome 7: SP survey respondents

Figure 6.6: Selectivity / Response Survey Process
To jointly model SP survey responses and the six binomial decisions in Figure 6.6, a multivariate probit or logit model should be implemented. Some procedures were implemented in this dissertation using different multivariate probability distributions, FGM (Mari and Kotz, 2001; Kolev et al., 2006; Nelsen, 2006) and Normal, in two software packages (R and Stata). These procedures were either not able to converge or generated estimates that do not represent the maximum of the likelihood function (Hessian matrix was not positive definite).

One of the main complexities in the estimation of multilevels models is that the correlation matrix of a multivariate normal distribution has to be positive semidefinite, meaning that $v'Cv \geq 0$, where $C$ is the correlation matrix and $v$ is any column vector. This constraint defines a surface in a hypercube $[-1,1]^k$, where $k$ is the number of levels, that restricts the space of feasible values of the parameters. For instance, in the bivariate case all region of the hypercube can be explored while for a fourvariate only 18.3% can be explored (Rousseeuw and Molenberghs, 1994).

There are some formulations using Bayesian Estimation or Expectation-Maximization Algorithm that might be able to estimate the full model (Ashford and Sowden, 1970; Albert and Chib, 1993; Chib and Greenberg, 1998; Cappellari and Jenkins, 2003; Edwards and Allenby, 2003; Cappellari and Jenkins, 2006; Tabet, 2007). The development of a specific formulation, including the development of an algorithm, to estimate the full model using these advanced statistical methods is out of scope of this dissertation since there are no standard ways to estimate this model for several response types (Bethlehem et al., 2011).

As stated earlier, a joint model is not feasible using available data, thus an approach was developed implementing a weighting adjustment. The objective is to identify a weight for each company $i$ that should be used in the estimation process. The procedure developed is based on the response propensity weighting (Bethlehem et al., 2011) and it assumes that the response propensity (probability) can be estimated satisfactorily using survey data. Therefore, the missing mechanism is called missing at random and responses in the survey can represent nonresponses (Bethlehem et al., 2011).
First, it is calculated how many companies a company \( i \) is representing in each stratum \( q \) \( (n_{iq}) \). The number is equal to the inverse of the sample fraction of stratum \( q \) \( (f_q) \) presented in Tables 4.1 to 4.3, see Equation (6.9).

\[
n_{iq} = \frac{1}{f_q}
\]  

(6.9)

Only companies that are active in the freight market, shippers, and select carriers based on price and other attributes are included in the SP survey (see Figure 6.6). Therefore, the expected value of the number of companies each company is representing in the SP survey sample can be calculated using the probability of the company being included in the SP survey, see Equation (6.10).

\[
E[n_{iq}] = \frac{P_i(A,S,PO)}{f_q}
\]  

(6.10)

where, \( P_i(A,S,PO) \) is the probability company \( i \) is included in the SP survey (active in the market, shipper, and select carriers based on price and others attributes).

The response propensity weighting consists of calculating a weight for each observation, \( w_i \), by multiplying the number of units one observation is representing by the inverse of the propensity (probability) of responding to the survey, see Equation (6.11). Therefore, this method increase the weight in the estimation process of companies with a lower probability of responding to the survey and it attempts to represent missing data with the data collected.

\[
w_i = \frac{E[n_{iq}]}{P_i(R)} = \frac{P_i(A,S,PO)}{P_i(R)f_q}
\]  

(6.11)

where, \( P_i(R) \) is equal to the propensity (probability) that company \( i \) would respond to the survey.

The weights used in the estimation of the carrier selection model incorporating the nonresponse bias correction, \( w_i^{EST} \), have to represent the same sample size of the original model, 482 observations (see Table 6.3), to permit the comparison between different approaches. Therefore, Equation (6.12) should be applied.
\[ w_i^{EST} = 482 \sum_{w_i} \frac{w_i}{w_i} \]  

(6.12)

Based on Equation (6.11), the weight adjustment still requires the estimation of the probability of responding to the survey and of being selected to participate in the survey. In this research, a nested logit model was estimated to represent the selectivity / response process in Figure 6.6. This model has partial degeneracy (Hunt, 2000) and binomial logit models on each level. The variables available are from the InfoCanada database and include industry classification (manufacturing, motor freight carrier or wholesale), sales volume, number of employees, city and distance to Toronto CBD. The parameters of these variables were included in a sequential estimation approach for nested logit models with joint estimation in the last step (Ben-Akiva and Lerman, 1985; Hensher, 1986; Hensher and Greene, 2002). The results are presented from Table 6.4 to Table 6.8. Only the levels of starting the survey and being a shipper were encountered to be nested.

**Table 6.4: Selectivity / Response Model Results: Level Contacted**

<table>
<thead>
<tr>
<th>Level Contacted</th>
<th>Est.</th>
<th>St. Error</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_{C,Const} )</td>
<td>-0.0933</td>
<td>0.0834</td>
<td>-1.1193</td>
</tr>
<tr>
<td>( \beta_{C,Manuf} )</td>
<td>0.2402</td>
<td>0.0731</td>
<td>3.2841</td>
</tr>
<tr>
<td>( \beta_{C,MotFreigCar} )</td>
<td>-0.1908</td>
<td>0.0826</td>
<td>-2.3091</td>
</tr>
<tr>
<td>( \beta_{C,SalesValue} )</td>
<td>-0.0014</td>
<td>0.0007</td>
<td>-1.9215</td>
</tr>
<tr>
<td>( \beta_{C,North.York} )</td>
<td>0.1698</td>
<td>0.1144</td>
<td>1.4845</td>
</tr>
<tr>
<td>( \beta_{C,Scarborough} )</td>
<td>-0.2654</td>
<td>0.1165</td>
<td>-2.2781</td>
</tr>
<tr>
<td>( \beta_{C,Brampton} )</td>
<td>-0.1976</td>
<td>0.1303</td>
<td>-1.5165</td>
</tr>
<tr>
<td>( \beta_{C,Etobicoke} )</td>
<td>-0.1745</td>
<td>0.1322</td>
<td>-1.3200</td>
</tr>
<tr>
<td>( \beta_{C,distCBD} )</td>
<td>0.0064</td>
<td>0.0023</td>
<td>2.7451</td>
</tr>
<tr>
<td>( L(0) = -2,800.09 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( L(\beta) = -2,773.67 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( p^2 = 0.009 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(-2(L(0) - L(\beta)) = 52.84 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \text{AIC} = 5,565.39 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( n = 4043 )</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 6.5: Selectivity / Response Model Results: Level Eligible

<table>
<thead>
<tr>
<th>Level Eligible</th>
<th>Est.</th>
<th>St. Error</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_{E,\text{Const}} )</td>
<td>0.2017</td>
<td>0.0781</td>
<td>2.5813</td>
</tr>
<tr>
<td>( \beta_{E,\text{Manuf}} )</td>
<td>-0.1697</td>
<td>0.1011</td>
<td>-1.6788</td>
</tr>
<tr>
<td>( \beta_{E,\text{MotFreigCar}} )</td>
<td>0.4397</td>
<td>0.1237</td>
<td>3.5544</td>
</tr>
<tr>
<td>( \beta_{E,\text{Mississauga}} )</td>
<td>0.2199</td>
<td>0.1179</td>
<td>1.8643</td>
</tr>
<tr>
<td>( \beta_{E,\text{Scarborough}} )</td>
<td>-0.2113</td>
<td>0.1710</td>
<td>-1.2357</td>
</tr>
<tr>
<td>( \beta_{E,\text{Toronto}} )</td>
<td>-0.3863</td>
<td>0.1777</td>
<td>-2.1738</td>
</tr>
<tr>
<td>( \beta_{E,\text{Markham}} )</td>
<td>0.7162</td>
<td>0.2252</td>
<td>3.1807</td>
</tr>
<tr>
<td>( L(0) = -1,414.02 )</td>
<td>( L(\beta) = -1,373.61 )</td>
<td>( \rho^2 = 0.029 )</td>
<td></td>
</tr>
<tr>
<td>-2(( L(0) - L(\beta) )) = 80.81</td>
<td>AIC = 2,761.29</td>
<td>n = 2040</td>
<td></td>
</tr>
</tbody>
</table>

Table 6.6: Selectivity / Response Model Results: Level Started Survey and Shipper

<table>
<thead>
<tr>
<th>Level Started the Survey</th>
<th>Est.</th>
<th>St. Error</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_{S1,\text{Const}} )</td>
<td>-2.7314</td>
<td>0.5522</td>
<td>-4.9464</td>
</tr>
<tr>
<td>( \beta_{S1,\text{MotFreigCar}} )</td>
<td>1.7340</td>
<td>0.5592</td>
<td>3.1010</td>
</tr>
<tr>
<td>( \beta_{S1,\text{Etobicoke}} )</td>
<td>-0.9844</td>
<td>0.4235</td>
<td>-2.3244</td>
</tr>
<tr>
<td>( \beta_{S1,\text{Markham}} )</td>
<td>-0.8323</td>
<td>0.4344</td>
<td>-1.9162</td>
</tr>
<tr>
<td>( \lambda_{S1} )</td>
<td>0.4455</td>
<td>0.2116</td>
<td>2.056</td>
</tr>
<tr>
<td>Level Shipper</td>
<td>Est.</td>
<td>St. Error</td>
<td>t-Stat</td>
</tr>
<tr>
<td>----------------</td>
<td>--------</td>
<td>-----------</td>
<td>---------</td>
</tr>
<tr>
<td>( \beta_{S2,\text{Const}} )</td>
<td>2.0533</td>
<td>0.2850</td>
<td>7.2056</td>
</tr>
<tr>
<td>( \beta_{S2,\text{MotFreigCar}} )</td>
<td>-4.8295</td>
<td>0.5679</td>
<td>-8.5049</td>
</tr>
<tr>
<td>( \beta_{S2,\text{Scarborough}} )</td>
<td>-1.6904</td>
<td>0.9468</td>
<td>-1.7855</td>
</tr>
<tr>
<td>( \beta_{S2,\text{Brampton}} )</td>
<td>0.8059</td>
<td>0.8863</td>
<td>0.9093</td>
</tr>
<tr>
<td>( \beta_{S2,\text{Etobicoke}} )</td>
<td>1.6118</td>
<td>1.1974</td>
<td>1.3461</td>
</tr>
<tr>
<td>( \beta_{S2,\text{Markham}} )</td>
<td>1.4067</td>
<td>1.4105</td>
<td>0.9973</td>
</tr>
<tr>
<td>( L(0) = -993.97 )</td>
<td>( L(\beta) = -638.29 )</td>
<td>( \rho^2 = 0.358 )</td>
<td></td>
</tr>
<tr>
<td>-2(( L(0) - L(\beta) )) = 711.37</td>
<td>AIC = 1289.73</td>
<td>n = 1195</td>
<td></td>
</tr>
</tbody>
</table>

Table 6.7: Selectivity / Response Model Results: Level Price and Others

<table>
<thead>
<tr>
<th>Level Price and Others</th>
<th>Est.</th>
<th>St. Error</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_{P,\text{Const}} )</td>
<td>3.2580</td>
<td>0.8650</td>
<td>3.7663</td>
</tr>
<tr>
<td>( \beta_{P,\text{Mississauga}} )</td>
<td>-1.7456</td>
<td>0.6403</td>
<td>-2.7263</td>
</tr>
<tr>
<td>( \beta_{P,\text{Scarborough}} )</td>
<td>-2.8360</td>
<td>1.4345</td>
<td>-1.9769</td>
</tr>
<tr>
<td>( \beta_{P,\text{Etobicoke}} )</td>
<td>-2.5491</td>
<td>1.0579</td>
<td>-2.4096</td>
</tr>
<tr>
<td>( \beta_{P,\text{distCBD}} )</td>
<td>-0.0294</td>
<td>0.0205</td>
<td>-1.4379</td>
</tr>
<tr>
<td>( L(0) = -78.33 )</td>
<td>( L(\beta) = -45.74 )</td>
<td>( \rho^2 = 0.456 )</td>
<td></td>
</tr>
<tr>
<td>-2(( L(0) - L(\beta) )) = 65.17</td>
<td>AIC = 102.05</td>
<td>n = 113</td>
<td></td>
</tr>
</tbody>
</table>
Table 6.8: Selectivity / Response Model Results: Level Able to Answer SP

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Est.</th>
<th>St. Error</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{A.\text{Const}}$</td>
<td>3.3732</td>
<td>0.5727</td>
<td>5.8900</td>
</tr>
<tr>
<td>$\beta_{A.\text{EmployeesValue}}$</td>
<td>-0.0257</td>
<td>0.0178</td>
<td>-1.4423</td>
</tr>
<tr>
<td>$\beta_{A.\text{SalesValue}}$</td>
<td>-0.1382</td>
<td>0.0339</td>
<td>-4.0732</td>
</tr>
<tr>
<td>$\beta_{A.\text{EmployeesValueSalesValue}}$</td>
<td>0.0022</td>
<td>0.0004</td>
<td>4.8303</td>
</tr>
</tbody>
</table>

$L(\theta) = -65.16$  
$L(\beta) = -29.44$  
$\rho^2 = 0.548$

$-2(L(\theta) - L(\beta)) = 71.43$  
AIC = 67.33  
n = 94

These results were applied to calculate the probability of being selected for companies that were classified on outcomes 1, 3, or 6. The distribution of the probability of being selected for these companies is presented in Figure 6.7. Using these probabilities, the expected proportion of nonrespondents that can be eligible (selected) to participate in the survey is 38.6%. Therefore, the nonresponse bias might be relevant in the final results of this model.

![Figure 6.7: Distribution Probability of Selection: Nonrespondent Companies](image)

Using this weighting adjustment, a carrier selection model was estimated and the results are presented in Table 6.9. Comparing these parameters with values in Table 6.3, there is a reduction in most parameter values that ranges from -45 to -20%. The only exception is the parameter of the scale function ($\gamma_{\text{ScalePar}}$), which increased 28% in this model.
Table 6.9: Heteroskedastic Selection Model: with Nonresponse Bias Analysis

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Value</th>
<th>Std.Error</th>
<th>t value</th>
<th>% Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{\text{CarRep5}}$</td>
<td>0.1477</td>
<td>0.0715</td>
<td>2.0656</td>
<td>-27%</td>
</tr>
<tr>
<td>$\beta_{\text{CarRep7}}$</td>
<td>0.1941</td>
<td>0.0820</td>
<td>2.3667</td>
<td>-31%</td>
</tr>
<tr>
<td>$\beta_{\text{QualDriv7}}$</td>
<td>0.1763</td>
<td>0.0751</td>
<td>2.3476</td>
<td>-21%</td>
</tr>
<tr>
<td>$\beta_{\text{HeliServComp}}$</td>
<td>-0.0170</td>
<td>0.0065</td>
<td>-2.6211</td>
<td>-27%</td>
</tr>
<tr>
<td>$\beta_{\text{Equipment95%}}$</td>
<td>-0.2578</td>
<td>0.1244</td>
<td>-2.0717</td>
<td>-25%</td>
</tr>
<tr>
<td>$\beta_{\text{Equipment90%}}$</td>
<td>-0.2025</td>
<td>0.1121</td>
<td>-1.8073</td>
<td>-25%</td>
</tr>
<tr>
<td>$\beta_{\text{Equipment90%}}$</td>
<td>-0.1647</td>
<td>0.1045</td>
<td>-1.5756</td>
<td>-22%</td>
</tr>
<tr>
<td>$\beta_{\text{DelRel}}$</td>
<td>0.4411</td>
<td>0.2932</td>
<td>1.5042</td>
<td>-45%</td>
</tr>
<tr>
<td>$\beta_{\text{LossDamProd}}$</td>
<td>-7.3978</td>
<td>2.8770</td>
<td>-2.5714</td>
<td>-25%</td>
</tr>
<tr>
<td>$\beta_{\text{PastExp3}}$</td>
<td>-0.3963</td>
<td>0.1797</td>
<td>-2.2051</td>
<td>-27%</td>
</tr>
<tr>
<td>$\beta_{\text{PastExp5}}$</td>
<td>-0.2605</td>
<td>0.1336</td>
<td>-1.9496</td>
<td>-20%</td>
</tr>
<tr>
<td>$\beta_{\text{PastExp7}}$</td>
<td>-0.1037</td>
<td>0.0980</td>
<td>-1.0578</td>
<td>-27%</td>
</tr>
<tr>
<td>$\beta_{\text{Price}}$</td>
<td>-1.4196</td>
<td>0.5972</td>
<td>-2.3771</td>
<td>-28%</td>
</tr>
<tr>
<td>$\beta_{\text{NoneASC}}$</td>
<td>-1.4944</td>
<td>0.6574</td>
<td>-2.2731</td>
<td>-20%</td>
</tr>
<tr>
<td>$\gamma_{\text{ScalePar}}$</td>
<td>0.3054</td>
<td>0.0895</td>
<td>3.4135</td>
<td>28%</td>
</tr>
</tbody>
</table>

$L(0) = -774.767$  \hspace{1cm}  $L(\beta) = -671.627$  \hspace{1cm}  $\rho^2 = 0.133$

$n = 83$ shippers  \hspace{1cm}  $N = 482$ obs  \hspace{1cm}  AIC($\beta$) = 1374.284

6.3.4. Heteroskedastic Selection Model: Complete Model

The non-attendance problem is analysed in this research using the approach proposed by Hensher and Greene (2010). Their approach assumes that individuals are classified into a set of \( Q \) classes. Classes in the non-attendance problem are represented by the set of attributes that are included in respondent decision process. For instance, in the carrier selection process, some respondents might not have included the attribute “price” in utility function. As consequence, carriers’ price values in the SP experiment do not influence their selection, and they would thus be placed in their own class.

Given this classification, the probability of choice \( j \) by individual \( i \) in choice situation \( t \) who is classified in class \( q \) in a multinomial logit model is given by Equation (5.1) (Hensher and Greene, 2010).

$$P_{it}[j \mid q] = \frac{\exp(x'_{it,j} \beta_q)}{\sum_{j=1}^{J} \exp(x'_{it,j} \beta_q)} \hspace{1cm} (6.13)$$

The classification of individuals for the estimation of discrete choice models can be observed or proposed by the analyst, which is the case of estimation using segmentation (Ben-Akiva and
Lerman, 1985). This is not the case in the analysis of the non-attendance problem where the class of each respondent (attributes in the response process) is unobserved.

This survey implemented an approach to minimize the non-attendance problem. Nevertheless, since most of the respondents selected more than seven attributes as important or very important, the non-attendance problem should be analysed because respondents are not usually capable of considering many attributes at the same time when selecting an alternative (Pearmain and Kroes, 1990). This might be particular true in a web survey with company managers (Dillman, 2009).

Since the classification is not totally observed in the survey, only the probability that a respondent belongs to a class can be estimated. Let $H_{iq}$ denote the probability for class $q$ for respondent $i$. This probability can be calculated using a multinomial logit model (see Equation (6.14)). Using this specification, one of the vectors of parameters should be normalized to zero ($\theta_q = 0$) to secure identification of the model.

$$H_{iq} = \frac{\exp(z_i' \theta_q)}{\sum_{k=1}^{Q} \exp(z_i' \theta_k)} , \ q = 1, \ldots, Q$$  \hspace{1cm} (6.14)

where $z_i$ denotes a vector of observable characteristics that enter the model for class membership.

The log likelihood for the sample is presented in Equation (6.15) (Hensher and Greene, 2010). Hensher and Greene (2010) called this specification a latent class model, which is regularly used in marketing applications (Train, 2009), and proposed the estimation to be implemented using traditional maximum likelihood estimation techniques, which was used in the model presented in this chapter.

$$\ln L = \sum_{i=1}^{N} w_i^{EST} \ln P_i = \sum_{i=1}^{N} \ln \left( \sum_{q=1}^{Q} H_{iq} \prod_{t=1}^{T} P_{it}[j \mid q] \right)$$  \hspace{1cm} (6.15)

Weights calculated in Section 6.3.3 are used in the estimation and therefore this model incorporates the analysis of both potential sources of errors in the SP survey: nonresponse bias and non-attendance problem.
In the SP experiment, up to ten attributes were included. The total number of $\theta_q$ parameter vectors estimated using this specification is $Q-1$. To restrict the number of additional parameters estimated using this specification, carrier selection models were estimated for four classes, with inclusion or exclusion of two attributes. The variable $z_i$ included in the expression for class membership probability (see Equation (6.4)) is sales volume of the shipper and the parameter vector of the class both attributes was fixed to zero. Many different combinations were analysed and the best result encountered was the specification for the inclusion/exclusion of price and delivery reliability attributes. The results are presented in Table 6.10.

Insignificant parameters are maintained in the model to permit the comparison with the results presented in Table 6.3 and 6.9, see Figures 6.8 a) to o). The $\rho^2$ increased from 0.13-0.14 in previous models to close to 0.23. Based on the AIC (Akaike Information Criteria), this model provides more accurate estimates than previous ones. Some parameter estimates are different to previous models:

- Equipment availability and past experience changed their sign. Five of six of these parameters changes from negative to positive sign. Values are closer to results in the first model than result in the model with nonresponse bias analysis
- Most of the parameters increased their value in this model when compared to previous models
- The probability of selecting both attributes (price and delivery reliability) is similar to the probability of selecting only delivery reliability for low values of sales volume. Bigger companies would increase the probability of selecting only no including price in the decision process
Table 6.10: Heteroskedastic Selection Model: Complete Model

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Value</th>
<th>Std.Error</th>
<th>t value</th>
</tr>
</thead>
<tbody>
<tr>
<td>β_{CarRep5}</td>
<td>0.2976</td>
<td>0.1339</td>
<td>2.2234</td>
</tr>
<tr>
<td>β_{CarRep7}</td>
<td>0.3802</td>
<td>0.1465</td>
<td>2.5954</td>
</tr>
<tr>
<td>β_{QualDriv7}</td>
<td>0.2898</td>
<td>0.1096</td>
<td>2.6426</td>
</tr>
<tr>
<td>β_{FolServComp}</td>
<td>-0.0306</td>
<td>0.0098</td>
<td>-3.1247</td>
</tr>
<tr>
<td>β_{EquipAvail85%}</td>
<td>0.3648</td>
<td>0.4107</td>
<td>0.8882</td>
</tr>
<tr>
<td>β_{EquipAvail90%}</td>
<td>0.4445</td>
<td>0.4219</td>
<td>1.0536</td>
</tr>
<tr>
<td>β_{EquipAvail95%}</td>
<td>0.5656</td>
<td>0.4271</td>
<td>1.3242</td>
</tr>
<tr>
<td>β_{DelRel}</td>
<td>1.9449</td>
<td>0.6189</td>
<td>3.1423</td>
</tr>
<tr>
<td>β_{LossDamProd}</td>
<td>-13.1857</td>
<td>4.3161</td>
<td>-3.0550</td>
</tr>
<tr>
<td>β_{PastExp3}</td>
<td>-0.1304</td>
<td>0.3299</td>
<td>-0.3953</td>
</tr>
<tr>
<td>β_{PastExp5}</td>
<td>0.1534</td>
<td>0.3301</td>
<td>0.4648</td>
</tr>
<tr>
<td>β_{PastExp7}</td>
<td>0.4529</td>
<td>0.3542</td>
<td>1.2789</td>
</tr>
<tr>
<td>β_{Price}</td>
<td>-2.9172</td>
<td>1.0203</td>
<td>-2.8591</td>
</tr>
<tr>
<td>β_{NoneASC}</td>
<td>-4.0802</td>
<td>1.4630</td>
<td>-2.7889</td>
</tr>
<tr>
<td>β_{NoneSalVol}</td>
<td>-1.5253</td>
<td>0.5195</td>
<td>-2.9359</td>
</tr>
<tr>
<td>γ_{ScalePar}</td>
<td>0.1645</td>
<td>0.0766</td>
<td>2.1485</td>
</tr>
<tr>
<td>α_{PriceYDelRelN}</td>
<td>-0.0245</td>
<td>0.0476</td>
<td>-0.5144</td>
</tr>
<tr>
<td>α_{PriceNDelRelY}</td>
<td>0.0405</td>
<td>0.0264</td>
<td>1.5329</td>
</tr>
<tr>
<td>α_{PriceNDelRelN}</td>
<td>-38.8346</td>
<td>1398.1019</td>
<td>-0.0278</td>
</tr>
</tbody>
</table>

L(0) = −774.767  L(β) = −598.888  \(\rho' = 0.227\)

n = 83 shippers  N = 482 obs  AIC(β) = 1237.420

![Graphs](image-url)
Three models were developed in this chapter to represent carrier selection by shippers. All models included a parameter to represent heteroskedasticity between shippers based on sales volume (size of shipper). This parameter was significant in all models and this result demonstrate that either bigger shippers have a more deterministic behaviour in selecting carriers than smaller shippers or bigger shippers answered the survey with more accuracy.

The first model uses a multinomial logit formulation to model carrier selection. The only labelled alternative in the SP survey (“None of Them”) had a negative alternative-specific constant. This result demonstrates the attractiveness of the hypothetical alternatives presented to the respondent. Attributes that represent general carrier evaluation in the market, carrier reputation and shipper past experience with the carrier, had significant parameters. They represent the impact of carrier interactions in the market in establishing a market power (Tirole, 1988), a competitive advantage over other carriers. For instance, carrier reputation is a measure of the impact of the brand name of the carrier in the market.
The second model incorporates a weighting adjustment for nonresponse bias. This adjustment seeks to increase the weight of respondents with a low probability of responding to the survey and, therefore, representing nonrespondents more appropriately. The results showed that there is an overestimation of the parameters in the utility function and an underestimation of the scale parameter if only respondent sample without weights are used in the estimation, which indicates the existence of nonresponse bias in the responded sample.

The third model analyses the non-attendance problem using a latent class model. Results showed that bigger companies may not consider carrier’s price in their carrier selection process. This conclusion is only valid for the range of prices presented in the SP survey, within 10% of market price average. Also, this result may explain the increase in the estimated values of the parameters in the utility function because shippers may increase their focus on other carrier attributes if they do not consider price to be relevant.
Chapter 7

Conclusions and Discussions

7.1. Final Concluding Remarks

This research project represents a contribution to a subject that is still in its early stages of knowledge. Current freight modelling approaches are not able to represent the complexities of actual freight markets. Since the characteristics of freight markets directly influence vehicle flows, current freight modelling approaches may not be able to accurately predict the impacts of transportation policies in freight movements. To improve this situation, a new framework is presented in this dissertation and some of its elements are investigated empirically. The framework is named FREMIS (FREight Market Interactions Simulation).

The framework consists of an approach to simulate freight markets using rational (intelligent) agents. Agents obtain all information about other agents while interacting in the market. In the framework, information about other agents is used in agents’ decisions to contract services (shippers) and to present contract proposals (carriers).

Agents (shippers and carriers) participate in the freight market seeking to increase their utility/profit. Shippers increase their utility/profit by bundling shipments to reduce their delivery costs and by selecting carriers that maximize their utility, based on price and level of service attributes. Meanwhile, carriers present proposals for contracts based on their cost of delivering shipments in the contract and their probability of winning the contract.

The proposed framework permits the simulation of freight markets using agent-based approaches. These approaches are called “bottom-up” approaches and they do not require any assumption of equilibrium (Tefsatsion, 2003). As a consequence, they permit the analysis of the
conditions upon which complex economic markets (e.g. freight markets) converge or not to one or more equilibrium points (Ehrentreich, 2008).

Some agent-approaches have been used to simulate freight markets (e.g. Liedkte, 2009; Baindur and Viegas, 2011). However, they do not include a representation of all elements included in FREMIS. For instance, Liedtke (2009) does not include product differentiation and Baindur and Viegas (2011) do not include economies of scope/scale. These two elements (product differentiation and economies of scope/scale) are important in the analysis of the motivations for the size of companies in the market (Tirole, 1988). Therefore, these approaches may not be able to represent the impact of big companies (e.g. Purolator, FedEX) in the freight market.

In addition to that, current agent-approaches in freight market do not explicitly consider agent interactions. Hence, many common situations in a freight market (e.g. competition, failure of companies) cannot be represented using these approaches. The framework proposed in this dissertation can represent the competition between carriers in the freight market. Since carriers’ behaviour is developed using profit functions, the framework can also simulate the failure or establishment of new carriers in the market (firmography processes).

One of the main obstacles in the development of a feasible framework for an agent-based simulation of a freight market is the availability of data. FREMIS was developed in an interactive process with the objective of creating simultaneously a realistic representation of freight market dynamics, assuming that agents are rational, and a feasible data collection procedure. The survey conducted during this research project illustrates the data collection procedure required to implement FREMIS. With an initial sample of 4,000 respondents and using a web survey for company managers (see Chapter 4), which usually results in a low response rate especially with small incentives (Dillman, 2009), two demand models were estimated with consistent results which allow their implementation in FREMIS.

The first demand model presented is a shipment bundling model (see Chapter 5). The proposed shipment bundling model combines a probabilistic model to predict the probability of bundling two shipments in the market and a vehicle routing algorithm to combine shipments using the results from the probabilistic model. The expected output of applying this model is a realistic
representation of the bundling process since some market characteristics (e.g. spatial concentration of freight flows) might influence this process. The results of the probabilistic model support the initial assumption that distances between shipments and locations with a high concentration of freight movements (called freight poles in this research) are relevant in the decision of bundling two shipments. These results also demonstrate the relevance of economies of scope in the GTHA freight market.

The second demand model developed in this dissertation is a carrier selection model (see Chapter 6). Three models were developed during this research by incorporating or not incorporating nonresponse bias and non-attendance problem corrections. All these models tested the hypothesis that agents (shippers) are heterogeneous by defining a scale parameter function related to agent company size (using sales volume). All models supported the agent heterogeneity hypothesis with significant parameter estimates. Therefore, we may have heterogeneous agents in the market unless they answered the survey in a different way. The incorporation of nonresponse bias and non-attendance problem corrections resulted in different models for the values of the parameters.

To best of the knowledge of this thesis author, this research presents the first attempt to model these two freight agent decisions using behavioural formulations. There are many models for freight mode choice but they are different when compared to carrier selection models. A freight mode choice model concentrates all carriers that uses the same mode in one group and treat them as homogeneous agents. Therefore, this model is not able to represent the dynamics in the freight market such as competition for contracts of carrier using the same mode. The other decision, shipment bundling, has not been analysed using probabilistic models. This might be related to the complexity of representing this decision in a SP survey or to collect all the information associated with this decision (e.g. all combinations of shipments included in the choice set) in a revealed preference (RP) survey.
7.2. Future research

During this research project, various elements were identified that will require a deeper investigation to permit the implementation of FREMIS framework in freight market simulation:

1) **Study carrier price strategy using probabilistic models:** FREMIS was developed assuming that carriers define their bid in contract proposals using a deterministic approach. This approach has been used in many agent-based market simulations (e.g. Ehrentreich, 2008). However, it might not be appropriate for freight markets. The main obstacle to propose an alternative approach is that company price strategies are one of the most difficult elements to predict (Talluri and van Ryzin, 2004) because many companies react to market situations in unexpected ways. For instance, a company may present a lower bid than expected to remove another company from the market or to increase its market power by reducing competition.

2) **Analyse agent rational behaviour assumption:** FREMIS was developed based on the assumption of rational agents. Even though this might represent actual behaviour in the market, since the marketing strategies of companies are increasingly supported by computational tools (e.g. revenue management, online freight auctions), in some situations agents probably do not follow any specific rational model. For instance, small carriers might lower their bid in contract proposals to an irrational level (negative profit) to increase their market share. This research agenda is related to the previous one.

3) **Extend the framework for medium and long-run carrier decisions:** FREMIS included only one short-run decision in the supply side, carrier bids in contracts. To permit the analysis of medium to long-run policies, the framework should be expanded to include other carrier decisions such as acquisition of new vehicles /fleet or construction of new facilities (e.g. terminals).

4) **Implement a survey to develop a complete shipment bundling model:** the probabilistic shipment bundling model presented in this dissertation can only include two shipments simultaneously. To develop a model to incorporate more shipments, a survey should be
implemented where many shipments are presented to shippers / carriers and their bundling decisions are collected. This survey should be well planned to minimize respondent burden. Since the number of possible combinations of shipments increases exponentially (see Equation (5.1)), the maximum number of shipments that can be reasonably presented in a webservice is low (e.g. 5 shipments can be combined in 52 ways). One possible approach is to first identify the individual response process for each respondent and customize the survey presenting only feasible bundles (combinations) of shipments.

5) Implement a qualitative survey to validate carrier attributes included in carrier selection processes: the attributes included in the SP survey were obtained in a literature review of carrier selection. Traditionally, the attributes in a SP survey should be defined based on qualitative survey, which was not implemented during this research due to limitation in resources. Also, the set of attributes may change for different type of shippers and different type of commodities.

6) Analyze the correlation between observations in the Carrier Selection Model: the Carrier Selection Model was developed assuming that the correlation between observations could be considered negligible with the adopted heterokedastic model specification. Since some correlation among observations from the same respondent may still exist, modelling frameworks (e.g. panel data for discrete models) that can analyze these correlations are currently being investigated for future research projects.

7) Develop carrier cost functions related to performance of the transportation system: the performance of the transportation system (e.g. travel time variability, average speed) has a direct impact in the operating costs of carriers (more congestion $\rightarrow$ more costs). The development of cost functions that are sensitive to the performance of the transportation system will facilitate the evaluation of transportation policies since these functions will be included into FREMIS implementation.

8) Analysis of the relationship between carriers’ level of service and the performance of the transportation system: the performance of the transportation system might have a relationship to carriers’ level of service. The existence of this relationship depends on how
carriers adapt themselves to the characteristics of the transportation system. For instance, if carriers are able to predict the maximum travel time for most of their deliveries, then they will have a high reliability, an important element of carriers’ level of service.

9) **Implement FREMIS in a freight market**: this is the main future research agenda. The models developed in this research can be used to implement FREMIS in the GTHA freight market. For that, parameters in the carrier profit function (e.g. cost parameters) should be estimated from secondary data and the scale parameters in the demand models should be estimated during the calibration of FREMIS outputs to observed data (e.g. freight flows). Another requirement is the availability of data from a commodity survey.

10) **Perform Equilibrium Analysis using the outputs of FREMIS implementation**: one of the analyses that can be performed using the outputs of FREMIS is Equilibrium Analysis. The framework to implement this Equilibrium Analysis has not been formulated yet. However, one approach that can be used is to identify Nash Equilibriums and under what conditions the market converges to these equilibrium points or not. In Nash equilibriums, players (carriers) do not have an incentive to change their strategy because it would reduce their payoff (profit). The formulation presented in this thesis only considered one strategy for carriers: a pricing strategy. Therefore, if carriers are using the same pricing strategy for different contracts then we can consider that they are in a Nash Equilibrium.
References


Metrolinx, 2011. GTHA Urban Freight Study, s.l.: s.n.


Appendix 1: Survey Questions and Descriptive Statistics

1) Question Q1

![Screenshot Question 1 (Q1) Layout: Respondent Type](image)

Figure A.1: Screenshot Question 1 (Q1) Layout: Respondent Type

![Pie chart showing respondent type](image)

Figure A.2: Respondent Type (Q1)
2) Questions: Q1C and Q1S

Figure A.3: Screenshot Question 1C (Q1C) Layout: Carrier Selection Process

Figure A.4: Screenshot Question 1S (Q1S) Layout: Carrier Selection Process

a) Q1C (132 valid responses)

b) Q1S (115 valid responses)

Figure A.5: Carrier Selection Process (Q1C and Q1S)
3) Questions: Q2C and Q2S

![Survey Page](image)

Figure A.6: Screenshot Question 2C (Q2C) Layout: Characteristics of One Shipment
To continue with the survey, we would like to have some information about one shipment of your company. Please describe it below. (Click for help)

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<th>Description</th>
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<td>City</td>
<td>Select a state first</td>
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<tr>
<td>City</td>
<td>Select a state first</td>
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<tr>
<td>Mode of transportation</td>
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<tr>
<td>Value of Shipment</td>
<td>(do not use commas, use only digits)</td>
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<tr>
<td>Type of Shipment</td>
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<tr>
<td>Commodity Weight</td>
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<td>Unit</td>
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<tr>
<td>Commodity Type</td>
<td>Click to select</td>
</tr>
<tr>
<td>NMFC (National Motor Freight Classification) Class</td>
<td>Click to select</td>
</tr>
<tr>
<td>Shipment frequency in your company (closest value)</td>
<td>Click to select</td>
</tr>
<tr>
<td>In your opinion, what would usually be the price charged by a carrier to deliver this shipment (in Canadian Dollars)</td>
<td>CAN$</td>
</tr>
<tr>
<td>What is the usual travel time between origin and destination for this shipment</td>
<td>Travel time:</td>
</tr>
<tr>
<td>How often does your company outsource (hire another company for) the delivery of this shipment</td>
<td>Click to select</td>
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</table>

Figure A.7: Screenshot Question 2S (Q2S) Layout: Characteristics of One Shipment
Figure A.8: Characteristics of One Shipment (Q2C and Q2S): Locations

Figure A.9: Characteristics of One Shipment (Q2C and Q2S): Mode of Transportation
Figure A.10: Characteristics of One Shipment (Q2C and Q2S): Type of Shipment

Figure A.11: Characteristics of One Shipment (Q2C and Q2S): Type of Commodity
Figure A.12: Characteristics of One Shipment (Q2C and Q2S): NMFC Class

a) Shipper (n = 105)

b) Carrier (n = 109)
Figure A.13: Characteristics of One Shipment (Q2C and Q2S): Shipment Frequency

Figure A.14: Characteristics of One Shipment (Q2C and Q2S): Frequency of Outsourcing
4) Question 3C (Q3C)

Figure A.15: Screenshot Question 3C (Q3C) Layout: Carrier’s Attributes Values

Figure A.16: Question 3C (Q3C) Layout: Follow-up Service Complaints
Figure A.17: Question 3C (Q3C) Layout: Billing Accuracy

Figure A.18: Question 3C (Q3C) Layout: Equipment Availability
Figure A.19: Question 3C (Q3C) Layout: Response to Problems
5) Question Q4C

Suppose that your company is competing with other carriers for 7 shipments contracts (shown in the table below) in an open auction in Toronto. The shipment is these contract is the shipment you provided information before.

In the auction, the lower bid and all bids up to 10% higher than the lower bid are qualified for the second phase of the auction. In the second phase, the company with the best carrier service attributes is selected for each contract.

Based on that, in your opinion what would be for each contract: (1) First, if your company would be interest in the contract; (2) Second, if interested, your company’s bid (in Canadian) and your company’s probability (chance) of winning (0-100%)? (Click for help)

| Type of Commodity: Food Products | From: Toronto, Ontario, Canada; |
| From: Toronto, Ontario, Canada; | To: Montreal, Quebec, Canada; |
| To: Montreal, Quebec, Canada; | Mode: Passenger Car; |
| Mode: Passenger Car; | Weight: 50 kg; |
| Weight: 50 kg; | Value(SANC): $1,000 |

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<th>Shipments per Week</th>
<th>Number of the shipments (deliveries) in the Contract</th>
<th>Length of Contract</th>
<th>Interested?</th>
<th>Your Company’s Bid</th>
<th>Probability of winning (0 - 100%)</th>
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<td>1</td>
<td>One day</td>
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<td>10</td>
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<td>Once a week</td>
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<td>One month</td>
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Figure A.20: Screenshot Question 4C (Q4C) Layout: Carrier Bid in Contracts
6) Question 5C

Figure A.21: Carrier Operations (Q5C)
7) Question Q3S

For each of the carrier service attributes below, please provide the importance for your company: (Click for help)

The table and chart illustrate the level of importance for each carrier service attribute based on the responses from 88 participants. The importance levels are categorized as Lower than Important, Important, and Very Important.

Figure A.22: Screenshot Question 3S (Q3S) Layout: Carrier Attributes Level of Importance

Figure A.23: Carrier Attributes Level of Importance (Q3S)
8) Question Q4S

Figure A.24: Screenshot Question 4S (Q4S) Layout: SP Experiment

9) Question 5S (Q5S)

Figure A.25: Level in the Supply Chain (Q5S)
10) Question 6S (Q6S)

Figure A.26: Shipper Operations (Q6S)

11) Question Q2

Figure A.27: Screenshot Question 2 (Q2) Layout: Shipment Bundles
12) Question Q3

![Bar chart showing number of employees (Q3)](image)

**Figure A.28: Number of Employees (Q3)**

13) Question Q4

![Bar chart showing sales volume (Q4) in $106](image)

**Figure A.29: Sales Volume (Q4) in $106**
Appendix 2: SP Designs

Two Attributes: 3 Choice Sets and 3 Alternatives

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Three Attributes: 6 Choice Sets and 3 Alternatives

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Eight Attributes: 6 Choice Sets and 4 Alternatives

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