# Assessing Input Uncertainty in Commodity-Based Freight Demand Models

by

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## Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

**Abstract**

Freight demand models are a set of tools utilized for the forecasting, planning, analysis, and/or optimization of the movement of commodities, such as the billions-of-dollars-worth of goods and services that are moved annually in Canada, and they contain uncertainty. There are two types of uncertainty that affect freight demand models: input and model uncertainty. Input uncertainty is concerned with the fact that there is error in the data used as inputs to model transportation demand such as biased surveys, incomplete datasets, varying commodity and industry classifications, etc. Model uncertainty is concerned with the fact that the model specification and calibration/estimation may contain error such as omitted variables, inappropriate assumptions, simplifications, etc.

There is a lack of understanding surrounding the uncertainty of freight demand models. Regardless, these models are widely researched, developed, and applied without characterizing the uncertainty of typical data sources used as inputs. The contributions of the variation present in different inputs to the model results are unknown, making it impossible to know the robustness of the model outputs or how the results might be improved. The literature review revealed that the most common freight model classification system is based on the unit of demand generation, the most used freight demand models in the North American practice are commodity-based, and input uncertainty has a greater effect on transportation demand models. Thus, this thesis proposes a formal five-step framework (i.e., uncertainty source identification, distribution of source identification, simulation, estimation of output distributions, and analysis of results) to analyze the effects and propagation of input uncertainty on the uncertainty of the outputs in commodity-based freight demand models.

The framework is applied to an Aggregate-Disaggregate-Aggregate version of a strictly empirical commodity-based freight demand model used to analyze the effects the Comprehensive and Progressive Trans-Pacific Partnership on Canada’s trade infrastructure. Essentially, uncertainty for three inputs is introduced and a set of outputs is simulated through repeated simulation. The three inputs are high level supply chain characteristics, value-weight ratios, and domestic mode shares – each being an input to one sub-model of the freight demand model. Dispersion, confidence intervals, and performance against the outputs of an illustrative base case are explored. In general, the case study model generates consistent results to the base case when looking at the conclusions of aggregated outputs, despite the tendency to high variance of the disaggregated outputs and the poor results of the confidence interval analyses. Implementation of the framework generated insight on the accuracy of the case study model, and it highlighted the specific instances where the modeller needs to be more cautious of the results when using only point data, as in the illustrative base case.

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**List of Abbreviations**

| Acronym | Name |
|---|---|
| ADA | Aggregate-Disaggregate-Aggregate |
| CBSA | Canada Border Service Agency |
| CETA | Canada-European Union Comprehensive Economic and Trade Agreement |
| CFAF | Canadian Freight Analysis Framework |
| CFS | Commodity Flow Survey |
| CGE | Computable General Equilibrium |
| CLT | Central Limit Theorem |
| COV | Coefficient of Variation |
| CPC | Central Product Classification |
| CPI | Consumer Price Index |
| CPTPP | Comprehensive and Progressive Trans-Pacific Partnership |
| CUSMA | Canada-United States-Mexico Agreement |
| CVS | Commercial Vehicle Survey |
| DOE | Design of Experiments |
| EFTA | European Free Trade Association |
| FAF | Freight Analysis Framework |
| FAF5 | Freight Analysis Framework Version 5 |
| FTA | Free Trade Agreement |
| GSC2 | GTAP Sector Classification |
| GTAP | Global Trade Analysis Project |
| GTHA | Greater Toronto and Hamilton Area |
| HS | Harmonized System |
| I-O | Input-Output |
| ISIC | International Standard Industrial Classification |
| JB | Jarque-Bera Test |
| K-S | Kolmogorov-Smirnov Test |
| LHS | Latin Hypercube Sampling |
| MC | Monte Carlo |
| NHCRP | National Highway Cooperative Research Program |
| NPP | Normal Probability Plot |
| O-D | Origin-Destination |
| PC | Production-Consumption |
| PCE | Passenger Car Equivalent |
| QRFM | Quick Response Freight Manual |
| RCEP | Regional Comprehensive Economic Partnership |
| ROW | Rest of World |
| TTIP | Transatlantic Trade and Investment Partnership |
| RTM | Regional Transportation System Model |

| Acronym | Name |
|---|---|
| SACU | South African Customs Union |
| SCAG | Southern California Association of Governments |
| SCTG | Standard Classification of Transported Goods |
| SCTG2 | Standard Classification of Transported Goods-2 |
| SMILE | Strategic Model for Integrated Logistics Evaluation |
| SW | Shapiro-Wilk Test |
| TFTA | Tripartite Free Trade Area |
| TH 10 | Trunk Highway 10 |
| TISA | Trade and Services Agreement |
| TIUS | Truck Inventory and Use Survey |
| US | United States |
| VIUS | Vehicle Inventory and Usage Survey |

# Chapter 1. Introduction

## 1.1. Background

The economic importance of trade and trade infrastructure to Canada is massive. Exports and imports of goods and services in Canada were 32.13% and 34.09% as a percentage of Gross Domestic Product in 2018, respectively (WITS, n.d.-a). In comparison, these values were 12.22% and 15.33% for exports and imports, respectively, in the United States, which is Canada's closest neighbour and a large western economy (WITS, n.d.-b). Moreover, the Government of Canada (2017) revealed that one in six jobs depended on international commerce in 2017. In the budget of the same year, the Government of Canada allocated $10.1 billion over 11 years to the maintenance, expansion, and efficiency of trade and transportation corridors (Government of Canada, 2019). This substantial investment demonstrates the importance of both trade and its infrastructure to Canada. Consequently, Canada is continuously trying to expand the reach of its economy, increasing the importance of trade and trade infrastructure. There are fifteen free trade agreements (FTAs) currently enforced. Two of the latest FTAs to be enforced are the Comprehensive and Progressive Trans-Pacific Partnership (CPTPP), enforced in 2018, and the Canada-United States-Mexico Agreement (CUSMA), enforced in 2020 (Government of Canada, 2020). The CPTPP is an FTA between Canada and ten Asia-Pacific countries: Australia, Brunei, Chile, Japan, Malaysia, Mexico, New Zealand, Peru, Singapore, and Vietnam (Government of Canada, 2020).

Freight demand models are a set of tools utilized for the forecasting, planning, analysis, and/or optimization of the movement of commodities, such as the billions-of-dollars-worth of goods and services that are moved annually in Canada. Freight demand models are used by both private and public entities to incorporate freight movement considerations into the transportation planning process, usually with the goal of making informed investments or to develop related projects or policies (United States Department of Transportation, 2020). There are multiple approaches in the literature and in practice to modelling freight that are catered to different variables such as spatial reach (e.g., state-wide versus country-wide), type of analysis (e.g., forecasting and performance), unit of reference (e.g., vehicle-trips, or commodity flows), level of aggregation, etc. Typical applications of freight demand modelling include:

- describing base year freight flows and explaining their transport-related variables;
- forecasting of freight flows and alternative analysis;
- assessing the performance of existing or possible freight systems; and
- designing and optimizing freight transport systems (Tavassy & De Jong, 2014).

Freight demand modelling was recently used to quantify the impact of FTAs on Canada's domestic trade infrastructure. Bachmann (2017) studied this by extending a typical computable general equilibrium (CGE) simulation of the Canada-European Union Comprehensive Economic and Trade Agreement (CETA) through the estimation of high-level supply chain characteristics for trade flows. Jahangiriesmaili et al. (2018) expanded on this body of knowledge to assess the potential impact of CETA on Canada's transportation network through the estimation of before-and-after origin-destination (O-D) trade flows, mode shares, and transportation flows. The result of these efforts was a commodity-based freight demand model, capable of assessing the effects of FTAs on the transportation of international export/import of commodities throughout Canada.

This model, along with all other travel and freight demand models, has uncertainty related to its inputs and the models themselves (de Jong et al., 2007; Rasouli & Timmermans, 2012). Input uncertainty is concerned with the fact that there is error in the data used as inputs to model transportation demand such as biased surveys, planning and land-use model outputs, etc. Model uncertainty is concerned with the fact that the model specification and calibration/estimation may contain error such as omitted variables, inappropriate assumptions, simplifications, etc.

## 1.2. Problem Statement

Despite the enormous body of work surrounding transportation demand models, there is limited understanding of the uncertainty present in these models. A literature review yielded approximately sixty studies that investigated different sources of uncertainty in a multitude of transportation demand models, and a couple of land-use models. Most of these studies were ad-hoc and concerning only passenger travel demand models. Westin et al. (2016) present the only study that directly analyzed uncertainty in a freight demand model. Their study used sensitivity analysis by varying the production-attraction base matrices from -20% to 20% in increments of 10%, for a total of 5 runs, while keeping everything else constant in the commodity-based freight demand model, SAMGODS (Westin et al., 2016). The study concluded that model outputs contain uncertainty from the input uncertainty, but it did not formally quantify the uncertainty nor did it study its propagation through successive sub-models (Westin et al., 2016).

Consequently, a formal effort is needed studying the effects of uncertainty propagation through successive sub-models or functions of a model in the context of freight demand modelling. Zhao and Kockelman (2002) present the most comprehensive study into the propagation of uncertainty through successive sub-models of a travel demand model. The authors study a typical four-step passenger travel demand model by arbitrarily assigning univariate and multivariate distributions to inputs and parameters and running a Monte Carlo (MC) Simulation one hundred times to estimate the distribution of the outputs at each step (Zhao & Kockelman, 2002). However, the sources of uncertainty were related to passenger travel and no substantial effort was made to estimate the actual distributions of their input sources (Zhao & Kockelman, 2002).

There is a lack of understanding surrounding the uncertainty of freight demand models. Regardless, these models are widely researched, developed, and applied without characterizing the uncertainty of typical data sources used as inputs. The contributions of the variation present in different inputs to the model results are unknown, making it impossible to know the robustness of the model outputs or how the results might be improved.

## 1.3. Research Objectives

The goal of this thesis is to develop and implement a framework to analyze the effects and propagation of input uncertainty on the uncertainty of the outputs in a commodity-based freight demand model.

The objectives of this research are as follows:

- Review the literature on freight demand modelling to identify and classify research efforts and practical efforts on available modelling techniques.
- Review the methodologies used previously in uncertainty analysis of transportation demand models (passenger and freight).
- Develop a framework to study and quantify input uncertainty in commodity-based freight demand models.
- Quantify the propagation of uncertainty due to inputs in the model developed by Bachmann (2017) and Jahangiriesmaili et al. (2018).
- Evaluate the uncertainty associated with the freight impacts of FTAs in Canada using the CPTPP as a case study.

### 1.4. Research Scope

The scope of this research is limited to commodity-based freight demand models. The case study used as an application of the proposed framework is limited to the domestic trade infrastructure of Canada, namely exports, before and after signing the CPTPP. This application is done through the commodity-based freight demand model developed by Bachmann (2017) and Jahangiriesmaili et al. (2018) which is hereafter referred to as “the model”. The spatial scope of this model is two-fold: 1) the economic model depicts international export/imports (with aggregations that include all regions of the world) with a focus on Canada, 2) the freight model allocates those international trade flows to Canada’s domestic trade network.

The temporal scope is introduced through the period of the model’s analysis and the variation applied to two of the model’s input variables. The first temporal scope is from 2015 to 2035 (20 years) which is the period in which the model is used to analyze the impacts of the CPTPP on Canadian trade infrastructure. The second temporal scope is introduced through the six-year variation of the data used to calculate the shares that disaggregate country-to-country trade flows resulting from the economic model forecast. The six years available for the Canada Border Service Agency (CBSA) data are 2010, 2011, 2012, 2013, 2014, and 2015. Lastly, the data used to calculate shares that aggregates the disaggregated trade flows into domestic flows (province-to-province) is varied over 7 years. The years available for the Canadian Freight Analysis Framework (CFAF) data are 2011, 2012, 2013, 2014, 2015, 2016, and 2017.

The scope includes the following two primary areas of contribution. The first contribution is a framework to quantify the propagation of uncertainty due to input uncertainty through a commodity-based freight demand model. The second contribution is the quantification of the propagation of uncertainty due to input uncertainty of the only model in Canada that estimates the effects of free trade agreements on the domestic transportation network using the CPTPP as a case study.

The scope of this thesis has two important boundaries. Firstly, uncertainty due to model specification or model estimation is not studied since the framework only analyzes input uncertainty. Secondly, the research presented does not study any other type of freight demand model such as trip-based or activity-based models.

Due to the above-mentioned scope boundaries, this research contains the following limitations. It is assumed that the model to which the framework is applied has been correctly specified and estimated since model uncertainty is not studied. However, the nature of model development necessitates simplifying assumptions, which are likely to induce some additional error. Nonetheless, studies on passenger demand models have concluded that input uncertainty has greater effects than model uncertainty on the outputs of the model (e.g., de Jong et al., 2007). Another limitation stems from not studying uncertainty in activity-based models. Activity-based models are different from trip-based and commodity-based models in that they are stochastic; thus, the propagation of their uncertainty necessitates its own framework. For example, in the passenger travel demand literature, a large portion of the research effort has been dedicated to quantifying the effects of stochastic simulation error as opposed to input uncertainty or other forms of model uncertainty (i.e., specification and estimation) (Castiglione et al., 2003; Cools et al., 2011; Gibb & Bowman, 2007; Lawe et al., 2009).

### 1.5. Structure of Thesis/Thesis Organization

This thesis is organized in five major sections. Chapter 1 is the introduction. Chapter 2 contains the findings of the literature review. Chapter 3 outlines the methodologies both for the proposed framework and its application to the case study. Chapter 4 presents and discusses the results. Chapter 5 contains the major conclusions, the limitations of the research, and possible future research topics.

Chapter 1 introduces the study. The background provided explains the importance of trade in Canada, introduces freight demand models, and briefly describes the development of the model used in the case study. The problem statement, research objectives, and research scope define the purpose, desired outcomes, and limitations of this study.

Chapter 2 presents the literature review. It is divided in three sections according to the aims of the review. The first aim is to identify current types of freight demand modelling techniques. The second is to establish the model type most widely used in practical applications in North America. The last aim is to identify uncertainty analysis techniques used in transportation demand models. Observations are presented in relation to those three aims.

Chapter 3 presents the methodology behind the framework and its application to the case study. In addition, the case study model is defined prior to explaining the application of the framework. The case study model, an aggregate-disaggregate-aggregate version of an entirely data-driven approach to the traditional four-step commodity-based model, is introduced. Then, a five-step framework is proposed to assess the uncertainty of the outputs of a commodity-based freight demand model due to the uncertainty of its inputs along with its application to the case study model.

Chapter 4 presents the results, the analyses of the results, and their respective discussions. There are three types of outputs generated by the case study model that are explored using the framework. The first set of outputs are the three disaggregated outputs from the three sub-models that comprise the freight model used in the case study. The second set of outputs reproduces the aggregated results of the original model application. The case study model was previously used to analyze the effects of the CPTPP on Canada's trade infrastructure and major conclusions were based on aggregated tables (e.g., total tonnage by international transport model, port of exit, etc.). The last set of outputs contains two targeted analyses of the disaggregated data. Two single supply chains are selected. One explores the results of a non-signatory country of the CPTPP - United States - and the other explores the results of a supply chain primarily serving the signatories of the CPTPP.

Chapter 5 presents the conclusions. The conclusions are presented according to the research goal and objectives described in Section 1.3. Additionally, the major findings of the application of the proposed framework to the case study are summarized. Lastly, the limitations and future possible research topics are discussed.

# Chapter 2. Literature Review

This literature review has three aims: 1) to identify current types of freight demand modelling techniques; 2) to establish the model type most widely used in practical applications in North America; and 3) to identify uncertainty analysis techniques used in transportation demand models. A review of model types and their classifications systems is needed in order to use the correct terminology throughout this research. Additionally, a review of the freight demand models used in the United States' and Canadian practices is necessary to identify the most widely used model types, in order to ensure the developed framework is widely applicable. Lastly, a review of available research efforts regarding uncertainty analysis of transportation demand models is needed in order to identify possible methodological foundations and gaps in the literature.

The scope of this review consisted of using various journal indexing systems including SCOPUS, Google Scholar, Research Gate, and Science Direct. In addition, the indexing tool available through the University of Waterloo library, entitled OMMI, was used to simultaneously search all journals and documents accessible through the University. Additional information through different government websites in Canada and the United States was also collected.

The remainder of this chapter is organized into three subsections:

- Classification of Freight Demand Models
- Freight Demand Models in Canada and the United States
- Uncertainty Analysis of Transportation Demand Models

## 2.1. Classification of Freight Demand Models

There are ongoing discussions regarding best practices to classify freight demand models. For example, Winston (1983) divided models based on the level of aggregation of the data used to develop the models. Zlatoper and Austrian (1989) also followed the classification of aggregate versus disaggregate models presented by Winston (1983). Alternatively, Regan and Garrido (2001) divided their review based on both the nature of the data (aggregate or disaggregate) and the spatial scope (international, intercity/interregional, urban).

This section reviews the most popular classification systems discussed in the literature in order to present an all-encompassing perspective. The first classification system is based on spatial scope, the second is based on the unit of reference of the demand generation, and the third, the Model Class System, has been recently implemented in the United States.

### 2.1.1. Classification Based on Spatial Scope

The first classification system proposed in the literature is based on the spatial scope of the models. This includes model types divided based on whether they analyze international, regional, or local/urban systems.

The National Highway Cooperative Research Program (NHCRP) (2008) released a report regarding the state-of-the-art of freight modelling in the United States (US). The authors highlighted the need to differentiate between long (or intercity) and short distances (or local) because there are different factors affecting the movement of freight that depend on the transport distance (National Cooperative Highway Research Program, 2008). The report further divided long-distance, interstate freight movement into three categories according to the nature of the origin-destination (O-D) pairs (National Cooperative Highway Research Program, 2008):

- shipments with an O-D pair in a single state,
- shipments with an O-D pair in two states, and
- shipments with an O-D pair in two states passing through intermediate states.

Another good example of this classification system was described by Nuzzolo et al. (2013). Their classification system based on spatial scope included subcategories that separated aggregate versus disaggregate models (Nuzzolo et al., 2013). Figure 1 depicts their proposed classification system.

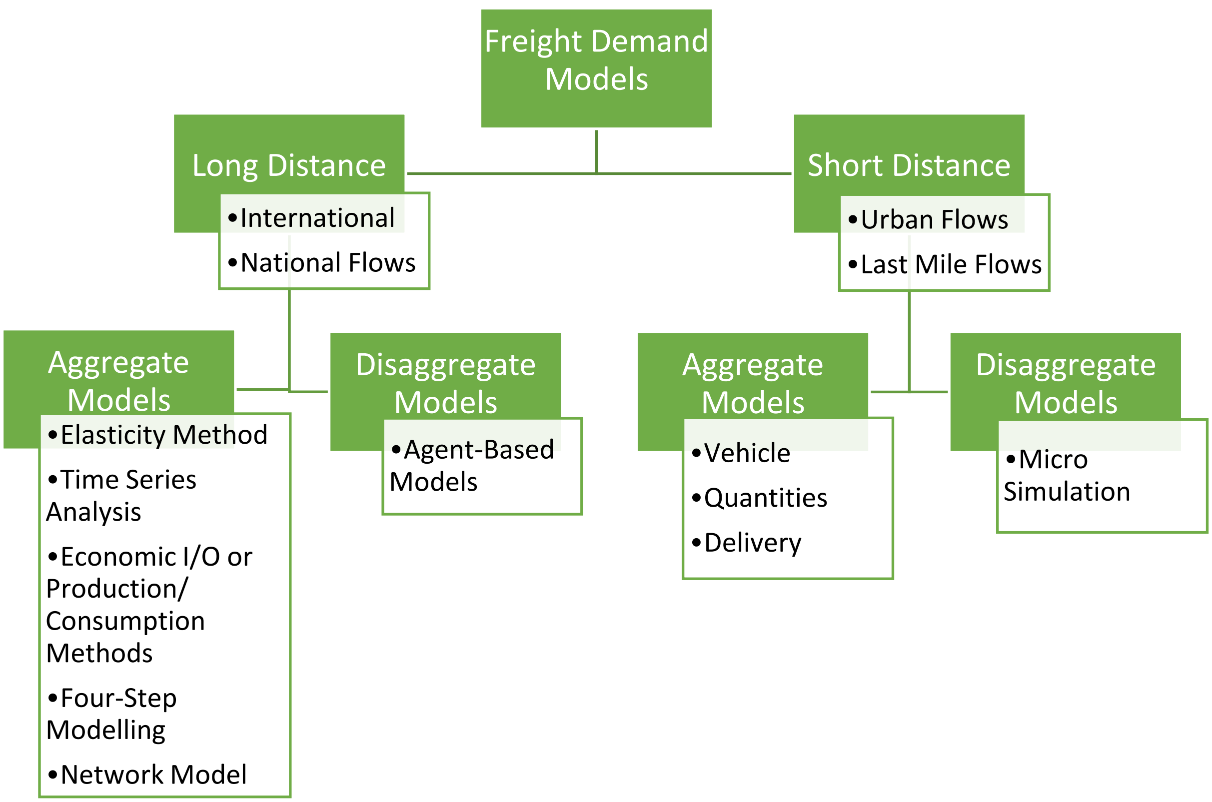


**Figure 1 Classification System Proposed by Nuzzolo et al. (2013)**

This classification system and the system based on unit of reference (see Section 2.1.2) are blurred when the authors further categorized long distance disaggregate models into agent-based models (Nuzzolo et al., 2013). Moreover, agent-based models are further divided based on the interactions between agents (i.e. carriers, shippers, and freight forwarders) that they consider, as seen in Figure 2 (Nuzzolo et al., 2013). The authors consider any model that incorporates some sort of agent behaviour as agent-based models and microsimulation is a specific set of agent-based models where the data to specify the model is already disaggregated.

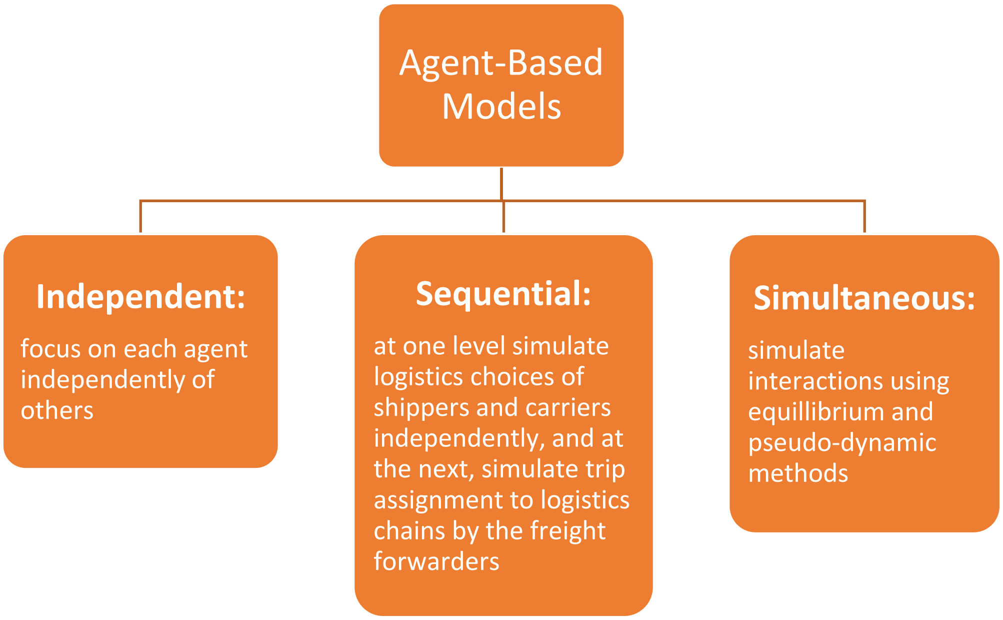


**Figure 2 Agent-Based Model Classification (Nuzzolo et al., 2013)**

The authors concluded that there is a trend towards agent-based models or disaggregate models that are harder to estimate and calibrate but incorporate key elements of freight movements such as shipper, carrier, and freight forwarders logistic decisions (Nuzzolo et al., 2013). Furthermore, at the short distance scale, they concluded that the literature has few models that examine the interactions between freight and passenger movement. They argued that this interaction is important due to congestion generated by both types of trips (Nuzzolo et al., 2013).

### 2.1.2. Classification Based on Reference Unit for Demand Generation

Referring to types of models based on the reference unit for demand generation is done throughout the literature (Chow et al., 2010; Fischer et al., 2005; Liedtke & Schepperle, 2004; National Cooperative Highway Research Program, 2008; Nuzzolo et al., 2013). Models classified by reference unit of demand generation include trip-based, commodity-based, and activity-based models.

For example, Nuzzolo et al. (2013) used this classification as subcategories to their proposed category of short distance aggregate models. In their vehicle-based models, the reference unit is a trip taken by a freight vehicle much like trip-based models. In their quantity-based models, the reference unit is the amount of a commodity which is similar to the commodity-based models. In their delivery-based models, the focus is on pick-ups and deliveries, which parallels the definition of activity-based models. However, as explained in the next paragraphs, this classification applies to all freight models and not only the ones developed for short distances with aggregated data (as used by Nuzzolo et al. (2013)).

*Trip-Based Models*

Trip-Based models generate production and attraction demand based on individual vehicle trips. These models only have three components (Figure 3) (Holguín-Veras & Thorson, 2000), akin to the vehicle-based models described by Nuzzolo et al. (2013). The mode choice step is not needed in these models because they only consider a single mode, which is usually trucks.

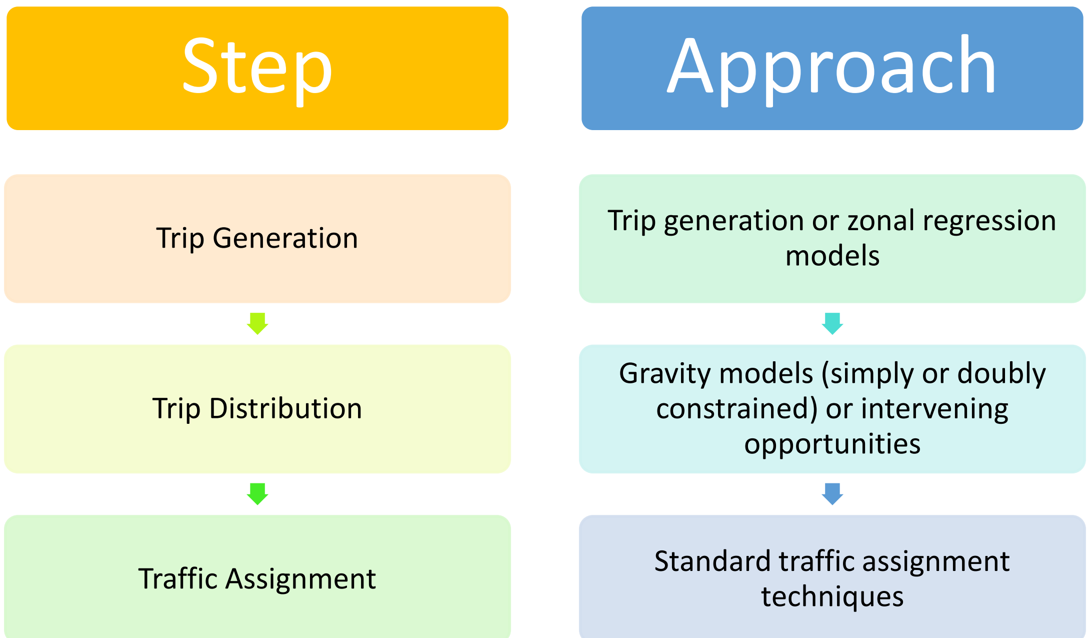


**Figure 3 Three-Step Trip-Based Models (Recreated) (Holguín-Veras & Thorson, 2000)**

Both advantages and disadvantages of these models are discussed in the literature. The benefits of using these types of models include: significant availability of data (traffic counts, screen counts, intelligent transportation retrofitting data, etc.), as well as less computational power required, and empty trips can be easily considered (Holguín-Veras & Thorson, 2000; Nuzzolo et al., 2013). One disadvantage of using trip-based models is their single modal nature which assumes that mode selection was previously done and consequently they do not account for other modes (Nuzzolo et al., 2013). Additionally, these models are not able to demonstrate the socio-economic and cargo characteristic variables behind mode selection, and do not take into account commodity production and attraction (Holguín-Veras & Thorson, 2000; Nuzzolo et al., 2013; Wisetjindawat et al., 2012).

*Commodity-Based Models*

Commodity-Based models have the commodity being transported as the reference unit of demand, relying on the idea that vehicle flows or trips are a result of the need for commodity movement (Holguín-Veras & Thorson, 2000; Wisetjindawat et al., 2012). These models often have the four components of the traditional four-step modelling approach but include a commodity production-attraction step (see Figure 4) instead of the usual vehicle trip generation. This step is used in order to better capture freight modelling economic mechanisms driven by cargo characteristics (Holguín-Veras & Thorson, 2000).

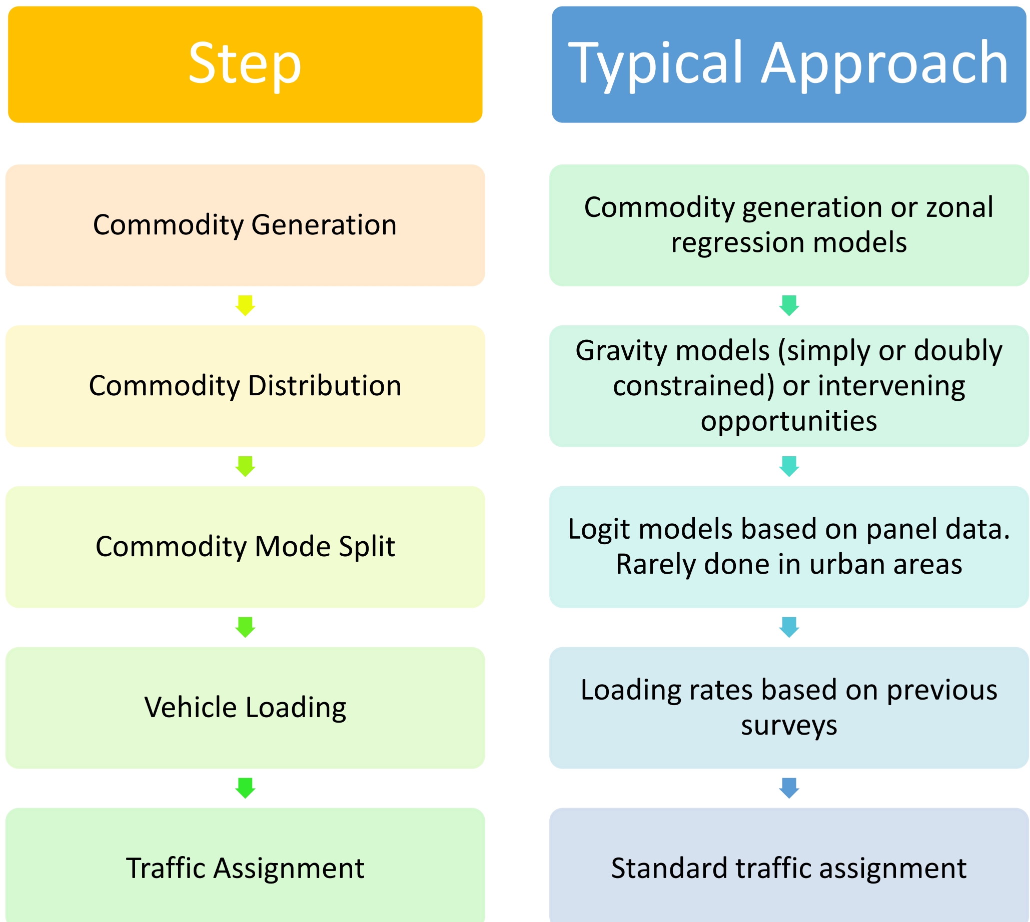


**Figure 4 Four-Step Commodity-Based Models (Recreated) (Holguín-Veras&Thorson, 2000)**

The vehicle loading step corresponds to the conversion between commodity flows and trips (Holguín-Veras & Thorson, 2000). Referring to quantity-based models, Nuzzolo et al. (2013) also explains this process. The quantities (or commodity flows) are generated by attraction models based on socio-economic data. Then, the quantities are spatialized, both in terms of O-D pair interactions and spatially dependent mode choices, using random utility models (RUM). Finally, the quantities are transformed into vehicle trips via additional steps (Nuzzolo et al., 2013).

A link to this classification system is found in the United States Model Class System. This system, which is explained in Section 2.1.3, contains two commodity-based classes of models: Class D The Four-Step Commodity Model and Class E Logistics Models (Chow et al., 2010; National Cooperative Highway Research Program, 2008).

Although commodity-based models are considered an improvement to trip-based models, there are multiple disadvantages of this modelling paradigm. Holguin-Veras and Thorson (2000) focus on the difficulties of modelling empty trips using commodity-based models. Empty trips are determined by freight movement logistics, the data for which are often not available to modellers (Holguín-Veras & Thorson, 2000). Some modellers have attempted to incorporate empty trips as a separate commodity, but this does not ensure the compatibility between total empty trips and total loaded trips, nor the influence of logistical attributes (Holguín-Veras & Thorson, 2000). Other disadvantages proposed by Fischer et al. (2005) are the lack of commodity flow data available at the traffic analysis zone level, and lack of local logistics data (deliveries, pick-up location, etc.). In addition, Liedtke and Schepperle (2004) as well as Chow et al. (2010) raised concerns regarding the crude conversions between commodity and vehicle flows because a formal and standardized approach to these conversions is missing. Additionally, while these models can be used to analyze changes in employment, modal utility, trip patterns, and network infrastructure, they do not take into account the interactions between freight industry decision makers or freight industry activities (e.g., logistics, tours, firm to firm relations etc.) (National Cooperative Highway Research Program, 2008).

*Activity-Based Models*

Activity-based or agent-based models consider freight activities or agents' behaviours as the primary generators of demand. Liedtke and Schepperle (2004) suggest the goal of activity-based models is to provide traffic planners with the tools to explain individual operational and logistical decisions, in order to analyze the effects of changes on transnational and federal transport policy. Multiple authors concluded that there is a trend of the current research towards developing activity-based models due to advances in computational power (Chow et al., 2010; Liedtke & Schepperle, 2004; National Cooperative Highway Research Program, 2008; Nuzzolo et al., 2013; Wisetjindawat et al., 2012). As alluded above, activity-based models need large, disaggregated agent/activity data which are often not publicly available. Consequently, these models are large, complicated, and require high performing computers and time to develop (Liedtke & Schepperle, 2004; Nuzzolo et al., 2013).

### 2.1.3. United States' Class System

In the US, NHCRP 606 report presented the Class System as a standardized way to classify all the existing freight modelling efforts used in practice by different states (National Cooperative Highway Research Program, 2008). Chow et al. (2010) updated the naming system and added short forms to the classes by categorizing them from A to E. The NHCRP 606 report highlighted modelling needs that the identified five classes did not meet and further stated that any single model class did not satisfy all freight modelling needs (National Cooperative Highway Research Program, 2008). Additionally, the report provided typical freight modelling components and concluded that Class A to E models share many of these components but differ in their organization and use (National Cooperative Highway Research Program, 2008). Table 1 shows the model classes included in NHCRP 606 report and their corresponding model components (in green).

**Table 1 Class System Differences According to Model Components (Recreated) (National Cooperative Highway Research Program, 2008)**

| Class | | Model Component | | | | | |
|---|---|---|---|---|---|---|---|
| | | Direct Factoring | Trip Generation | Trip Distribution | Mode Split | Traffic Assignment | Economic/ Land Use Modeling |
| **A** | **Direct Facility Flow Factoring Method** | 1 | | | | | |
| **B** | **O-D Factoring Method** | 2 | | | | | |
| **C** | **Truck Model** | | 3 | | 5 | | |
| **D** | **Four-Step Commodity Model** | | 3 | | | | |
| **E** | **Economic Activity Model** | | 4 | | | | |

[1] Direct factoring of facility flows.
[2] Direct factoring of O-D tables.
[3] Trip generation based on exogenously supplied zonal activity.
[4] Trip generation based on outputs of economic model.
[5] Not applicable because the mode is assumed to be trucks.

Fischer et al. (2005) separately conducted a review of the available types of models and identified two additional ones: Logistic Chain models and Tour-based models. Both of these types of models aim to better simulate interactions between the different decision makers in the movement of freight to assess policy making and impact assessment (Chow et al., 2010; Fischer et al., 2005). Chow et al. (2010) formally recognized seven model classes by adding the Class F: Logistics Chain Model and Class G: Tour-based models.

Class A, Direct Facility Flow Factoring Method, uses growth factors on available facility flow data for short-term forecasts (National Cooperative Highway Research Program, 2008). Models in this class are simple to implement and rely on regression equations from either a time series analysis or an economic analysis (National Academies of Sciences, 2008). The estimates of flow can be based on growth factors applied to data of flow within the facility or data of flow diversion to other routes or modes (National Academies of Sciences, 2008). Several assumptions must be made because the method does not consider many important factors and it also does not provide overall system forecasts (National Academies of Sciences, 2008).

Class B, Origin-Destination Factoring Method, uses growth factors on available O-D tables in order to perform conventional mode split and trip assignment using a newly generated O-D table (National Cooperative Highway Research Program, 2008). Economic, employment, or other indicators of zonal growth can be used to develop growth rates (National Cooperative Highway Research Program, 2008). The zonal growth factors are typically applied in an iterative manner to the O-D tables that proportionally fits and balances production and attraction growth rates (National Cooperative Highway Research Program, 2008).

Class C, The Truck Model, is also known as the three-step model because it uses three of the four steps in the conventional four-step model: trip generation, trip distribution, and trip assignment (National Cooperative Highway Research Program, 2008). The mode split step is not necessary because it only uses truck trips, and consequently, these models cannot analyze modal shifts (National Cooperative Highway Research Program, 2008). Truck models are typically use in conjunction with passenger cars to analyze flows on road links and are commonly used as part of urban travel forecasting models (National Cooperative Highway Research Program, 2008). Trucks types in the models are classified based on their gross vehicle weight into light, medium, and heavy, which loosely relate to other truck properties such as the number of units per truck (National Cooperative Highway Research Program, 2008).

Class D, The Four-Step Commodity Model, follows the traditional travel demand four-step model approach but the base unit is commodity flows obtained from economic forecasts instead of using passenger trips (National Cooperative Highway Research Program, 2008). These models require large amounts of data and time to develop, for example, they require statewide zone and network structures (National Cooperative Highway Research Program, 2008). It is difficult to develop utility information for modal split in freight modelling due to its complexity, thus, simple existing market mode shares are typically applied or adjusted in a qualitative manner (National Cooperative Highway Research Program, 2008). These models also require conversion from commodity tonnage or monetary value to equivalent trips depending on the mode split. In the NHCRP 606 report, the authors recommended using payload factors obtained from processing data in the Vehicle Inventory and Usage Survey (VIUS) or the Commodity Flow Survey (CFS) (National Cooperative Highway Research Program, 2008). However, the report also acknowledges that different models use varying methodology and data sources for these conversions (National Cooperative Highway Research Program, 2008). All the drawbacks of the commodity-based models, discussed in Section 2.1.2, apply to these models.

Class E, The Economic Activity Model, uses the typical four-step process but links the outputs of the freight model to economic forecasts and iterative methods are often used to jointly model their interactions (National Cooperative Highway Research Program, 2008). Like in Class D models, economic forecasts are inputs in this class of models (National Cooperative Highway Research Program, 2008). The difference is that the economic forecasts are updated using the performance outputs from the freight model (usually integrated with a passenger model); and then, the updated forecasts are fed back into the freight model creating a dynamic spatial input-output (I-O) model (National Cooperative Highway Research Program, 2008).

Class F, Logistics Models, simulate logistics choices by applying analytical methods (Fischer et al., 2005). Supply chains or distribution channels are simulated by incorporating multiple origin and destinations with intermediate stops (Chow et al., 2010). The base unit of these models are commodity flows instead of vehicle trips since supply chains follow a commodity from raw through finished product (Chow et al., 2010). The models under this category vary significantly and include both commodity-based models, for example the Strategic Model for Integrated Logistics Evaluation (SMILE), and activity-based models, such as Liedtke and Schepperle's freight model (Chow et al., 2010; Liedtke & Schepperle, 2004).

Class G, Tour-Based Models, are activity-based models that focus on tour characteristics of truck trips instead of the commodity characteristics (Fischer et al., 2005). These models intend to generate a more accurate evaluation of the vehicle movement and the decisions of carriers (Chow et al., 2010). The focus so far has been in truck modes, thus modal split analysis is not considered (Fischer et al., 2005).

## 2.2. Models in Canada and the United States

This section provides an overview of freight demand models used in Canada and the United States. Information on modelling practices is more readily available in the US context than in Canada. Thus, although the research presented in this thesis is based on a Canadian model, it is important to gather knowledge from a neighbouring country with similar characteristics.

Both countries developed integrated datasets regarding national freight movements which allocated commodity flows in origin-destination format. The Freight Analysis Framework (FAF) was developed in the US through a partnership between the Bureau of Transportation Statistics and the Federal Highway Administration (National Transportation Research Center et al., 2021). In its fifth version (FAF5), O-D datasets have been synthesized for the base year of 2017 containing information by region of O-D, commodity type, and mode (National Transportation Research Center et al., 2021). Data for the years of 2018-2019 and forecasts for the years 2020-2050 as well as previous years (1997-2012), both in increments of five years, will be available in later versions (National Transportation Research Center et al., 2021). Similarly, CFAF combined data available in Statistics Canada to produce datasets containing O-D data, shipment value, commodity type, number of shipments, weight transported, tonne-kilometers, revenue, and mode by province, by sub-areas such as Toronto, or by international destinations/origins (Statistics Canada, 2020). However, FAF5 has the ability to complete commodity flow network assignments on major road networks making it a freight demand model and not just an integrated database like its Canadian counterpart (National Transportation Research Center et al., 2021; Statistics Canada, 2020).

### 2.2.1. Models in Canada

The following is the result of exploratory research on freight demand models used in practice by different levels of governance across Canada. Regional, provincial, and territorial models were researched. It is important to note that this was a search on information available to the public online; and thus, it is not all-encompassing.

The Transport and Regional Economic Simulator of Ontario (TRESO) is a passenger, freight, and macroeconomic model developed for the Province of Ontario (Duggal et al., 2017). Freight demand modelling is handled by three sub-models: a commodity flow model, a long-distance truck model, and an urban truck tour model (Duggal et al., 2017). The commodity flow model uses 2011 Transport Canada data and 2012 Commercial Vehicle Survey (CVS) data to forecast flows (in units of weight) and identifies each commodity based on the Standard Classification of Transported Goods-2 (SCTG2) (Duggal et al., 2017). The commodity flows are then converted into truck trips and added into the long-distance truck model along with other truck data such as private trucks carrying company equipment (e.g., contractor tools) that are not otherwise considered commodities (Duggal et al., 2017). The truck touring model is a variation of the microsimulation truck touring model developed for Calgary by Hunt and Stefan (Damodaran, 2017; Hunt & Stefan, 2007).

Transport Quebec conducted a study to analyze the transportation of merchandise (freight) and it used a truck model to evaluate truck trips in the province (Transport Quebec, 2005). The model consisted of the standard trip generation, distribution and assignment steps. The model also had an added component created by MTO and IBI to detect travel inconsistencies and adjust them interactively (Transport Quebec, 2005).

The Greater Toronto and Hamilton Area uses the GTAModel, that is currently in version 4.1.0, which includes an integrated freight sub-model (Travelling Modelling Group, 2019). The holistic transportation demand model, GTAModel V4.1.0, handles passenger movement with a disaggregate activity-based model named TASHA that was validated for the Greater Toronto and Hamilton Area (GTHA) by Roorda et al. (2008) (Miller et al., 2015; Travelling Modelling Group, 2019). The freight demand sub-model is a truck model, much like the ones described under Class C Truck Models in Section 2.1.3, and it is based on a commercial vehicle model designed by Chowdhury and Roorda (see Figure 5) (Travelling Modelling Group, 2019; Tufayel & Roorda, 2020).

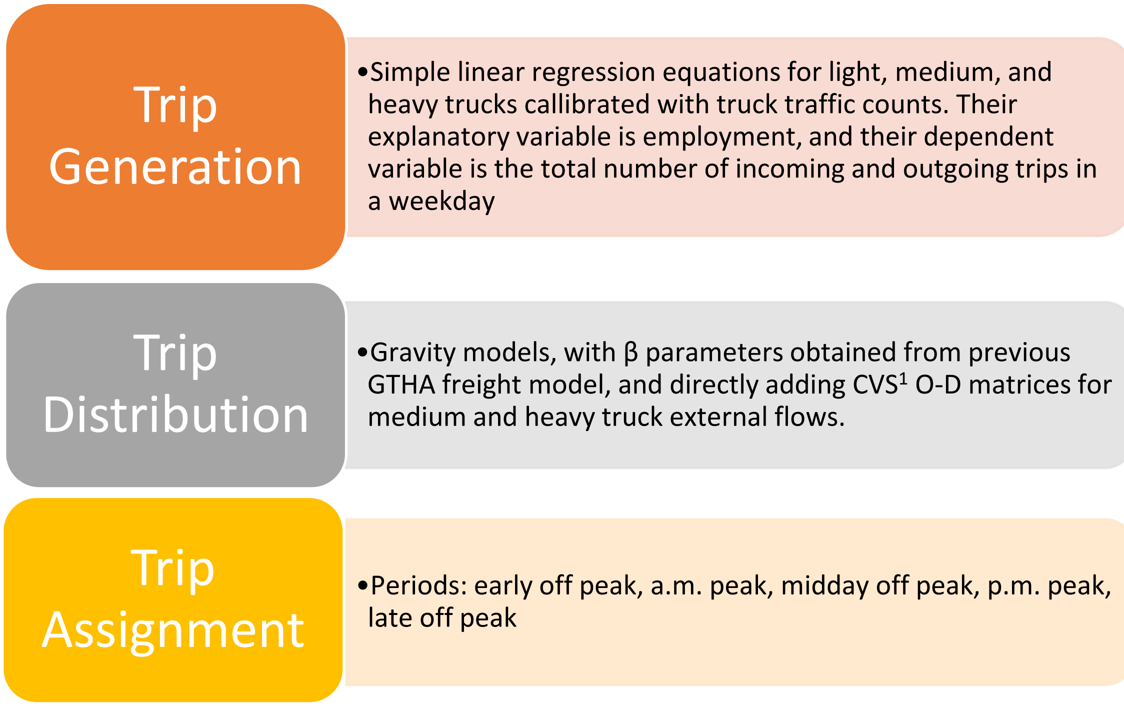


**Figure 5 GTAModel V4.1.0 Freight Demand Module Framework (Travelling Modelling Group, 2019)**

[1] Commercial Vehicle Surveys (CSV).

As part of the Lower Mainland Truck Freight Study, the Greater Vancouver/Fraser Valley Region developed a Truck Demand Forecasting Model as a sub-model of their EMME/2 Travel Demand Forecasting Model (TransLink, 2000). O-D surveys along with vehicle volumes and classification surveys were conducted in order to create the EMME/2 model between 1999 and 2000 (TransLink, 2000). The collected data, in addition to special generators data (e.g. Port of Vancouver, Vancouver International Airport, etc.), was used to link truck demand to demographic variables for forecasting AM peak hour or 24 hour period demand for the years 2006, 2011, 2021 (TransLink, 2000). The report disclosed that commodity flow analysis was not part of the development of this model (TransLink, 2000). Moreover, the specific framework of the model is not disclosed in the report.

The Calgary Region developed a tour-based microsimulation model to forecast urban freight movement as a sub-model to their Regional Transportation System Model (RTM) (National Academies of Sciences, 2008). The RTM is composed of a personal travel demand model, which is an aggregate equilibrium model, a commercial vehicle movement model, and a joint vehicle assignment process (National Academies of Sciences, 2008). The main source of data for model development was interviews about commercial vehicle movements collected in 2001 from own-account sources (National Academies of Sciences, 2008). Tour generation is done at an aggregate level, the rest of the steps in the framework are done through different Monte Carlo simulations, and lastly, the model iterates to “grow” the tours, see Figure 6 (National Academies of Sciences, 2008).

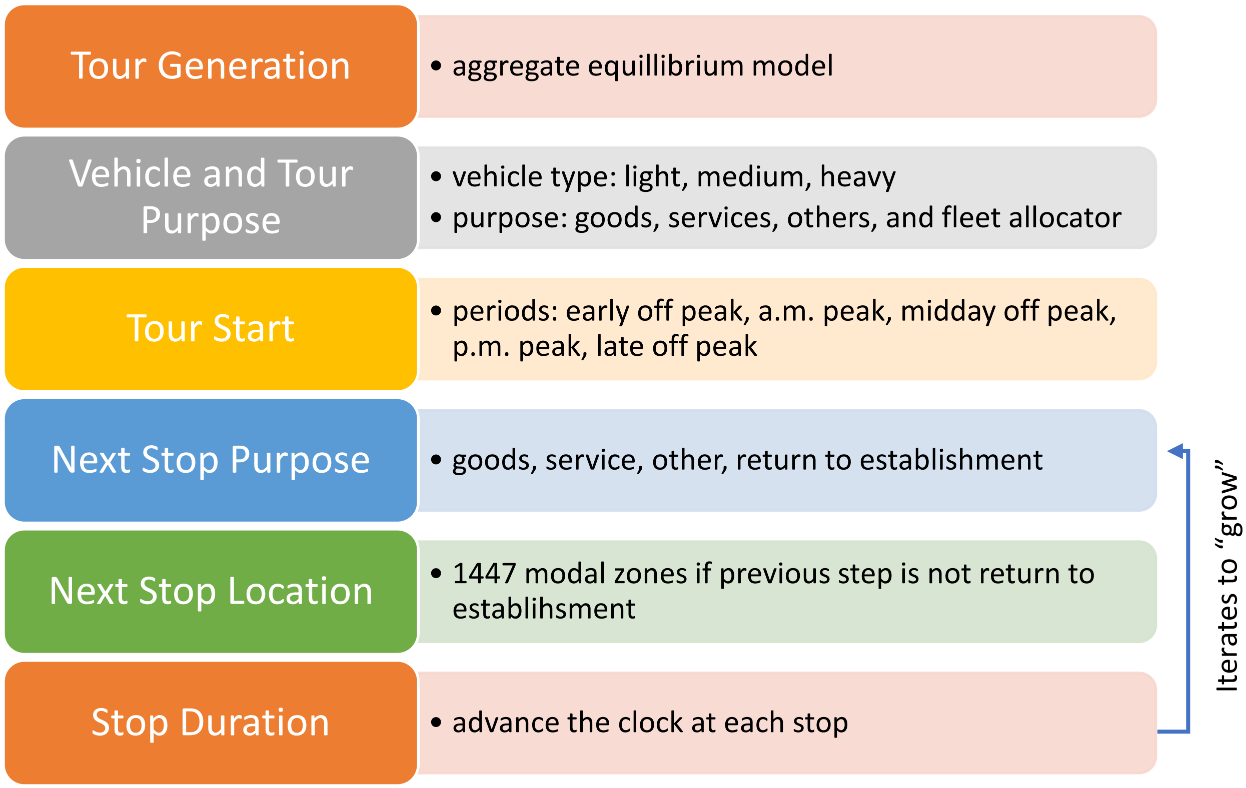


**Figure 6 Calgary Region Tour-Based Model Framework (National Academies of Sciences, 2008)**

The Ottawa-Gatineau Metropolitan area or National Capital Region developed a transportation forecasting model using EMME/4 which considers truck trips via truck O-D tables (MMM Group Limited, 2014b). Using an interprovincial truck survey conducted in 2007, truck/commercial O-D matrices were created as inputs for the EMME/4 model (MMM Group Limited, 2014b). The model is mainly focused on passenger movement, but it incorporated truck flows in the a.m. and p.m. peak periods assignment (MMM Group Limited, 2014b).

Several Canadian locations have limited or unavailable information regarding their freight demand modelling tools. The City of Winnipeg developed a transportation planning model using TransCAD; however, a study by MMM Group Limited (2014a) that used the model and expanded it to the Manitoba Capital Region disclosed that the model was unable to simulate movement of goods due to unavailability of truck data. According to Damodaran (2017), Transport Quebec conducted a study which led to a freight modelling methodology, however more information was not found; although, the organization offers passenger transport modelling (Transport Quebec, 2005). The same tour-based model used in Calgary was said to be being developed for Edmonton in conference proceedings of 2008 but more information was not found (National Academies of Sciences, 2008).

Other Canadian locations had freight demand models developed by researchers but no information on the models being used in practice was found. Rwakarehe et al. (2014) developed an I-O commodity-based model for the Province of Alberta in 2014 but information on practical implementation was not available. Similarly, Rwakarehe et al. (2015) developed a commodity-based model using data from the Province of Saskatchewan but no information on practical implementation was found. Bela and Habib (2019) developed a tour-based truck model for the City of Halifax in 2019, and the Halifax Regional Municipality expressed a need to incorporate freight movements into their Regional Transportation Demand model in a 2016 report, but no practical implementation was found (Davis Transportation Consulting, 2016). In the Northwest Territories, researchers used utility functions and logit models to assign mode shares along the Makenzie River Corridor in order to analyze the shift in shippers' decisions based on river water conditions (Du et al., 2017). Similar to the other examples, in this last case, no information on practical applications was found.

Table 2 is a summary of the models described above along with their corresponding model types based on the classification described in Section 2.1.2. The summary shows that the majority of the models used in practice are trip-based. However, general conclusions about the state-of-practice in Canada cannot be drawn since these are part of a small sample found in publicly available information and therefore may not be truly representative.

**Table 2 Summary of Freight Demand Models in Canada**

| Governance | Model Type | Model Name |
|---|---|---|
| GTHA | Trip-Based | Truck Model Demand Module as part of GTAModel V4.1.0 |
| Greater Vancouver/Fraser Valley Region | Trip-Based | Truck Demand Model (EMME/2) |
| Calgary Region | Activity-Based | Tour-based Microsimulation Model |
| Ottawa–Gatineau Metro | Trip-Based | Truck Trips O-D Tables |
| Halifax | Activity-Based | Tour-based urban truck model (like Calgary)* |
| Quebec | Trip-based | Truck Model |
| Alberta | Commodity-Based | I-O and Commodity-Based Four Step Model* |
| Ontario | Commodity-Based, Activity-based | Commodity Flow Model, Long-Distance Truck Model, Urban Truck Tour-Based Model |
| Saskatchewan | Commodity-Based | Commodity-based Model* |
| Northwest Territories | Activity-Based | Utility function and logit model* |

* Research studies developed these models for the governance context and no practical applications were found.

### 2.2.2. Models in the United States

This section provides some insight on the state of practice in the US regarding freight demand modelling. A few examples of models included in the National Cooperative Highway Research Program (NCHRP) 606 report are discussed as well as the relevant results of the comprehensive review in the subsequent NHCRP report from 2010 (National Cooperative Highway Research Program, 2008, 2010). The NHCRP 606 report provides case studies that include ten models, two per model class from Class A to Class D, used in practice by different states (National Cooperative Highway Research Program, 2008). In the toolkit, the case studies were all reviewed under the same headings: general modelling approach, model data (source and outputs), model development, model validation, model application, and performance measures and evaluation (National Cooperative Highway Research Program, 2008). A summary is presented in Table 3.

**Table 3 Models Used in Practice by US Government Bodies (National Cooperative Highway Research Program, 2008)**

| Class | Demand Generation | Name | Description |
|---|---|---|---|
| A | Truck trip-based | Minnesota Trunk Highway 10 Truck Trip Forecasting Model | Forecast model of corridor TH 10[1] that used historical truck data (1992-1999) and regional employment data along with growth factors derived as per the QRFM[2] |
| A | Truck trip-based | Heavy Truck Freight Model for Florida Ports | The model used truck flow data (1996-1998) in and out of the Port of Miami and linear regression to estimate the freight volume movement of the facility. Then, a time series analysis was used to examine forecasts. |
| B | Commodity-based | Ohio Interim Freight Model | Base year commodity O-D tables from TRANSEARCH[3] (1998) were factored using growth rates derived by mapping economic activity data to each commodity class in order to perform model split and network assignment[4]. |
| B | Commodity-based | Freight Analysis Framework | The national model used various public and proprietary datasets to develop commodity O-D tables at the national, state, and county levels for the base year of 1998 and forecasted years. Mode split was conducted using historical mode shares and highway network assignment was performed too[4]. |
| C | Truck trip-based | New Jersey Statewide Model Truck Trip Table Update | A statewide model that divided truck types by weight into medium and heavy. Demand was generated through employment-based equations and other identified special generators (ports, etc.). Standard techniques were used for trip distribution and assignment. |

| Class | Demand Generation | Name | Description |
|---|---|---|---|
| C | Truck trip-based | SCAG[5] Heavy-Duty Truck (HDC) Model | A combination of six counties developed a model that derived demand from a shipper and receiver survey and divided into categories based on employment and truck sizes. Some of the external trips are proprietary data that are in commodity flows which are then transformed into truck loads using the TIUS[6]. Trip distribution was done trough gravity models and assignment is divided by time periods (a.m. peak, midday, p.m. peak, night). Since this model is part of a Travel Demand Model, the trucks were converted to PCEs[7]. |
| D | Commodity-based | Indiana Commodity Transport Model | The model used standard four-step methods with data from the 1993 CFS. Conversion of flows was done using a different procedure than previously explained before the mode split step. Mode split included nine different modes and a separate model was used called NEWMODE. |
| D | Commodity-based | Florida Intermodal Statewide Highway Freight Model | This model followed the standards of a commodity four-step model. The data for conversions of money to weight and weight to trips were obtained using 1997 CFS, the Consumer Price Index and VIUS. |
| E | Commodity-based | Cross-Cascades Corridor Analysis Project | A combined passenger and freight economic integrated spatial I-O model. Trips were generated iteratively, and freight mode choice was handled with time-based costs much like passenger models. At the time of the report this model had not been applied |
| E | Commodity-based | Oregon Statewide Passenger and Freight Forecasting Model | The model generated demand/production from an activity location and transportation network interface, then a set of possible paths are identified to which commodity flows are converted to trips in an iterative process. The model had the ability to check returning empty vehicles. |

[1] Trunk Highway 10 (TH 10)

[2] Quick Response Freight Manual (QRFM) now know as the Quick Response Freight Methods in its 2019 edition. (Federal Highway Administration, 2019)

[3] TRANSEARCH is a privately owned US freight dataset used by multiple government bodies to develop models and forecasts. (IHS Markit, 2020)

[4] Flow conversions were done as explained under Class D models using VIUS data. (National Cooperative Highway Research Program, 2008)

[5] Southern California Association of Governments (SCAG) is an association of the counties of Los Angeles, Orange, San Bernadino, Riverside, Venture, and Imperial. (National Cooperative Highway Research Program, 2008)

[6] Federal Truck Inventory and Use Survey (TIUS) (National Cooperative Highway Research Program, 2008)

[7] Passenger car equivalent (PCE)

Another NHCRP (2010) report presented their findings on a state of practice review and compared them to the state of research in the US. The findings were clustered into eight categories that they proposed as a framework and the specific models were not disclosed. The categories are summarized below:

1. Time series models are based on historical or observed data and range from simple regressions models to complex multivariate autoregressive models.
2. Behavioural models capture how different agents (shippers, carriers, receivers, etc.) react and select from available freight shipment choices.
3. Commodity-based input-output models link economic activity data to freight flows and exhibit all the benefits and drawbacks of commodity-based models.
4. Multimodal network models assign freight flows to modes and routes by minimizing total transport costs.
5. Microsimulation models depict individual movements and agent-based models define a set of agents and their potential actions and interactions to preform "what-if" scenarios.
6. Supply and chain logistics models are as defined previously (National Cooperative Highway Research Program, 2008)
7. Network design models output optimal freight movement service based on frequency, mode, routing, and scheduling for freight logistic companies.
8. Routing and schedule models try to optimize those two attributes.

Table 4 below is a reconstruction of their findings with an added column categorizing their model groups into the ones proposed by the NHCRP 606 report and Chow et al. (Chow et al., 2010; National Cooperative Highway Research Program, 2008).

**Table 4 Review of Freight Demand Modelling in the US (National Cooperative Highway Research Program, 2010)**

| Model Category | Model Class | Model Development | Model implementation | Public Sector Applications |
|---|---|---|---|---|
| Time Series | A, B | ● | ● | ● |
| Behavioral | F, G | ◑ | ◑ | ◑ |
| Commodity-Based I-O | D | ● | ● | ● |
| Multimodal Network | D, F | ● | ◑ | ◑ |
| Microsimulation and Agent Based | F, G | ● | ● | ◑ |
| Supply Chain/Logistics | F | ● | ◑ | ○ |
| Network Design Models | F, G | ◑ | ○ | ○ |
| Routing and Scheduling | G | ◑ | ○ | ○ |

● Widely used/state of practice

◑ Emerging model/limited use

○ Lacking research/application

The 2010 report concluded that, while there are many advances in the literature, public sector applications are concentrated mostly on commodity-based variants of the traditional four-step approach or simple time series models (National Cooperative Highway Research Program, 2010).

### 2.3. Uncertainty Analysis

There are only a few instances where uncertainty analysis is applied to transportation demand models. Only one study was found during this review where uncertainty analysis was applied specifically to a freight demand model (Westin et al., 2016). Most of the research regarding this topic studied passenger travel demand models. For this reason, the majority of the discussion will be regarding passenger models in order to draw from their lessons learned and apply the knowledge to the context of freight demand modelling.

The section is divided into three subsections. First, a description of the main sources of uncertainty, as defined in the literature, is presented. Second, different methodologies used to analyze uncertainty are explored. Last, the current state of research is discussed.

#### 2.3.1. Uncertainty Sources

Uncertainty analysis in transportation demand models is concerned with the sources and propagation of uncertainty through the models due mainly to two sources: input uncertainty and model uncertainty (de Jong et al., 2007; Rasouli & Timmermans, 2012). De Jong et al. (2007)

concluded that in transportation models uncertainty is present because the values that forecasted variables will take in the future are unknown, which is also defined as dispersion. Input uncertainty is concerned with the fact that there is error in the data used as inputs to model transportation demand such as biased surveys, incomplete datasets, varying commodity and industry classifications, etc. (de Jong et al., 2007; Rasouli & Timmermans, 2012). Model uncertainty is concern with the fact that the model specification and calibration/estimation may contain error such as omitted variables, inappropriate assumptions, simplifications, etc. (de Jong et al., 2007; Rasouli & Timmermans, 2012). Input uncertainty was found to be more important than model uncertainty when uncertainty analysis was applied to the Dutch National and Regional passenger transport models (de Jong et al., 2007). Only a few papers have studied input uncertainty alone (e.g., Leurent, 1998; Rodier & Johnston, 2002) or model uncertainty alone (e.g., Brundell-Freij, 1997, 2000; Hugosson, 2005). Rather, most studies analyzed uncertainty due to both sources (e.g., Armoogum, 2003; Ashley, 1980; de Jong et al., 2007; Krishnamurthy & Kockelman, 2003; Kroes, 1996; Matas et al., 2012; Petrik et al., 2016; Pradhan & Kockelman, 2002; Zhang et al., 2011; Zhao & Kockelman, 2002). Moreover, the literature shows that, for activity-based models, the research effort has been mostly dedicated to uncertainty of the outcomes due to the randomness of the simulations (e.g., Castiglione et al., 2003; Cools et al., 2011; Gibb & Bowman, 2007; Lawe et al., 2009).

### 2.3.2. Uncertainty Analysis Methodologies

Methods for analyzing uncertainty within transportation demand models over the years have overwhelmingly included a form of repeated simulation using sensitivity analysis techniques, scenario analysis and variants of MC simulations (de Jong et al., 2007; Manzo, 2014; Rasouli & Timmermans, 2012; Westin et al., 2016). Analytical methods have also been used but are only known to work with simpler models (de Jong et al., 2007; Rasouli & Timmermans, 2012).

Different forms of sensitivity testing have been used in previous studies. Sensitivity testing consists of repeated model simulations while varying one or multiple input variables over a possible range; therefore, these tests are commonly used to analyze the effect of input uncertainty in model outcomes (de Jong et al., 2007). In activity-based models, sensitivity analysis has been used to identify influential parameters; for example, using one-at-a-time methods (e.g., Bao et al., 2016).

Scenario analyses are a form of repeated simulation (sensitivity testing) used to quantify the combined effect of uncertainty in the outputs due to varying multiple input variables according to a set of possible scenarios (de Jong et al., 2007; Westin et al., 2016). To develop scenarios, the researchers must identify which variables would have the greatest effect on the outcome of interest and what possible values the variables may take (Westin et al., 2016). Identifying possible correlations among the varied variables is important in order to maintain the scenarios internal consistency (Westin et al., 2016). A good methodology to achieve internal consistency is Morphological Analysis, described in Eriksson and Ritchey (2002) (Westin et al., 2016). Probabilities are often not attached to scenarios making it impossible to obtain uncertainty margins of the outputs.

MC simulation consists of random sampling that can be used to generate runs for sensitivity tests in order to study both input and model uncertainty (de Jong et al., 2007; Manzo, 2014; Westin et al., 2016). Input variables and/or model parameters are given known distributions from which random draws are taken and the model is run several times with a different set of random draws each time. Distributions for the model outcomes can be estimated based on the repeated simulations. Distributions for both input and model uncertainty variables are needed in order to use this methodology.

MC simulation has been used in the transportation modelling literature multiple times including Ashley (1980), Zhao and Kockelman (2002), Krishnamurthy and Kockelman (2003), De Jong et al. (2007), and Zhang et al. (2011). Most studies have assumed distributions types, and/or distribution parameters (e.g., Ashley, 1980; Krishnamurthy & Kockelman, 2003; Zhang et al., 2011; Zhao & Kockelman, 2002) for both types of uncertainty variables, which is problematic. A solution to these assumptions is using time series data to estimate the distribution of input variables and their correlations (Manzo, 2014). Another solution is to determine estimates of the distribution of the parameters (model uncertainty) from the calibration process or using re-sampling techniques, such as Jack-Knifing (see Quenouille (1949) for description and Armoogum (2003) for an applied example) and Bootstrap (e.g., Hugosson, 2005), using the original calibration dataset (de Jong et al., 2007; Manzo, 2014). Manzo (2014) provides a detailed description of these two resampling techniques in their literature review.

The randomness of MC simulations requires several runs that may be hard to accomplish with complicated transportation demand models. A solution to this problem is using stratified or quasi random sampling techniques such as Halton draws (e.g., de Jong et al., 2007), the Latin Hypercube Sampling (LHS) (e.g., Yang & Chen, 2009), or the Sobol Method which has only been discussed once in the transportation demand modelling context (e.g., Bao et al., 2016). Table 5 provides a summary of sampling and resampling techniques.

**Table 5 Summary of Sampling and Resampling Techniques**

| Technique | Description | e.g. |
|---|---|---|
| Monte Carlo | Random draws are taken from input/parameter distributions to use in repeated simulations | (Zhao & Kockelman, 2002) |
| LHS | Stratified random draws are taken from input/parameter distributions to use in repeated simulations.<br>The cumulative distribution of variables is divided into equal intervals and one random value is taken from each interval. | (Yang & Chen, 2009) |
| Halton Draws | Quasi-random draws are taken from input/parameter distributions to use in repeated simulations.<br>The quasi-random draws are based on a form of the Halton Sequence (Daly et al., 2003). | (de Jong et al., 2007) |
| Sobol Method | Quasi-random draws are taken from input/parameter distributions to use in repeated simulations.<br>The quasi-random draws are based on a form of the Sobol method explained in Saltelli (2002). | (Bao et al., 2016) |
| Jack-Knifing | Resampling method usually used, in this context, to recalibrate parameters by creating subsamples.<br>n +1 (where n is the original sample size) subsamples are created by subtracting one or more observations from the original sample at a time. | (Armoogum, 2003) |
| Bootstrap | Resampling method usually used, in this context, to recalibrate parameters by creating subsamples.<br>As many subsamples as possible are created by drawing n (where n is the original sample size) observations from a distribution of the original sample. This means that each observation has a probability of being drawn of 1/n and the subsample or bootstrap sample may contain repeated original sample observations or ones that appear zero times. | (Hugosson, 2005) |

Response surface methodologies have been used in combination with MC simulation in order to quantify the effects of uncertainty in the inputs for a selected outcome using simpler meta-models. Adler et al. (2014) used a response surface methodology approach consisting of one third of $3^3$ fractional factorial design (9 runs) to obtain a meta-model that explained the traffic forecast response in terms of three inputs. The distributions of the inputs were estimated using different datasets (Adler et al., 2014). The meta-model was then used in a MC simulation with several draws being possible due to the simpler nature of the meta-model when compared to the original travel demand model (Adler et al., 2014). Copperman et al. (2016) used a similar approach but with several more inputs. The authors first tested a fractional factorial three-level resolution IV design (81 runs) to assess possible two-factor interactions and concluded that these were counterintuitive (Copperman et al., 2016). Then, a smaller three-level fractional factorial test (27 runs), followed by a three-level probabilistic design (27 runs), and five full model runs were used to fit a meta-model (Copperman et al., 2016). Lastly, like in the previous study, the meta-model was used in MC simulations to get a distribution for the output (Copperman et al., 2016).

### 2.3.3. Uncertainty Analysis of Transportation Demand Models

This section describes the findings of two major review papers regarding uncertainty analysis in transportation demand modelling by De Jong et al. (2007) and Rasouli and Timmermans (2012). Additional insights regarding the propagation of uncertainty through successive models (Zhao & Kockelman, 2002) and a discussion of the only analysis of uncertainty performed on a freight demand model (Westin et al., 2016) are also included.

In their review paper, De Jong et al. (2007) identified 21 studies in the literature (up to 2007) that investigated uncertainty in passenger travel demand models. Most of the studies researched the effects of input uncertainty on model outputs and only nine were concerned with the effects of model calibration/specification uncertainty (or uncertainty in the estimation of parameters) (de Jong et al., 2007). Some form of repeated simulation was always used to quantify the amount of input uncertainty by specifying some statistical distributions (mostly univariate) and randomly, or at specific intervals, drawing input variables from these distributions (de Jong et al., 2007). The univariate distributions do not allow for correlation between input variables to be examined. The methodologies for quantifying model uncertainty were more varied and included analytical expressions if models were simple, sampling techniques (such as jack-knifing, bootstrapping), and variants of the Monte Carlo simulation. At the time of this review, only Zhao and Kockelman (2002) looked at the propagation of uncertainty through multiple sub-models.

De Jong et al. (2007) proposed preferred methodologies based on their review. They concluded that a natural approach to analyze uncertainty in input variables was a Monte Carlo simulation while including variable correlation (e.g., using multivariate normal distributions) (de Jong et al., 2007). In the case of model specification uncertainty, they proposed to use the jack-knife/bootstrap sampling techniques (de Jong et al., 2007). Lastly, to evaluate model estimation uncertainty, they concluded that a Monte Carlo simulation is preferred (de Jong et al., 2007).

Rasouli and Timmermans (2012) also presented a comprehensive review of uncertainty analysis in transportation demand models. Their paper summarized fifteen additions to the literature dividing them into four-step models, discrete choice models, and activity-based models (microsimulation and computational processes) (Rasouli & Timmermans, 2012). The authors concluded that, although the body of research regarding transportation demand forecasting is enormous, the research into uncertainty is scarce and not systematic, since the efforts differ greatly in methodologies (Rasouli & Timmermans, 2012). Most of the studies are ad hoc and vary a single source of uncertainty without a systematic approach or without identifying significant factors (Rasouli & Timmermans, 2012). The studies concentrated on the uncertainty of the outcomes with little attention paid to correlations between variables that affect travel demand (Rasouli & Timmermans, 2012). They also concluded that most studies used a univariate or multivariate (normal) distribution for variables but suggest that in some cases, such as free flow travel times used as inputs in activity-based models, this is not a good assumption (Rasouli & Timmermans, 2012). Finally, they echoed that for practical use, the effects on the outcome of models due to input uncertainties is the most valuable information, thus collecting data on input variability to generate better distributions would be helpful in the future (de Jong et al., 2007; Rasouli & Timmermans, 2012).

Zhao and Kockelman (2002) have the most substantial findings on the topic of error propagation through successive sub-models. In their research, distributions were assigned to inputs and parameters, which were then varied over 100 runs of a typical 4-step model (Zhao & Kockelman, 2002). The distributions of some inputs were assumed to be multivariate to account for some correlations (Zhao & Kockelman, 2002). The output distribution and variation were estimated from the results of the repeated simulations and quantified for each step of the model (Zhao & Kockelman, 2002). A multivariate regression analysis was then conducted to identify important contributors to overall uncertainty (Zhao & Kockelman, 2002). Their results showed that uncertainty is likely to compound itself over a series of successive sub-models using the mean, 95th, and 5th percentiles of the coefficients of variations (COVs) of the outputs (see Figure 7) (Zhao & Kockelman, 2002).

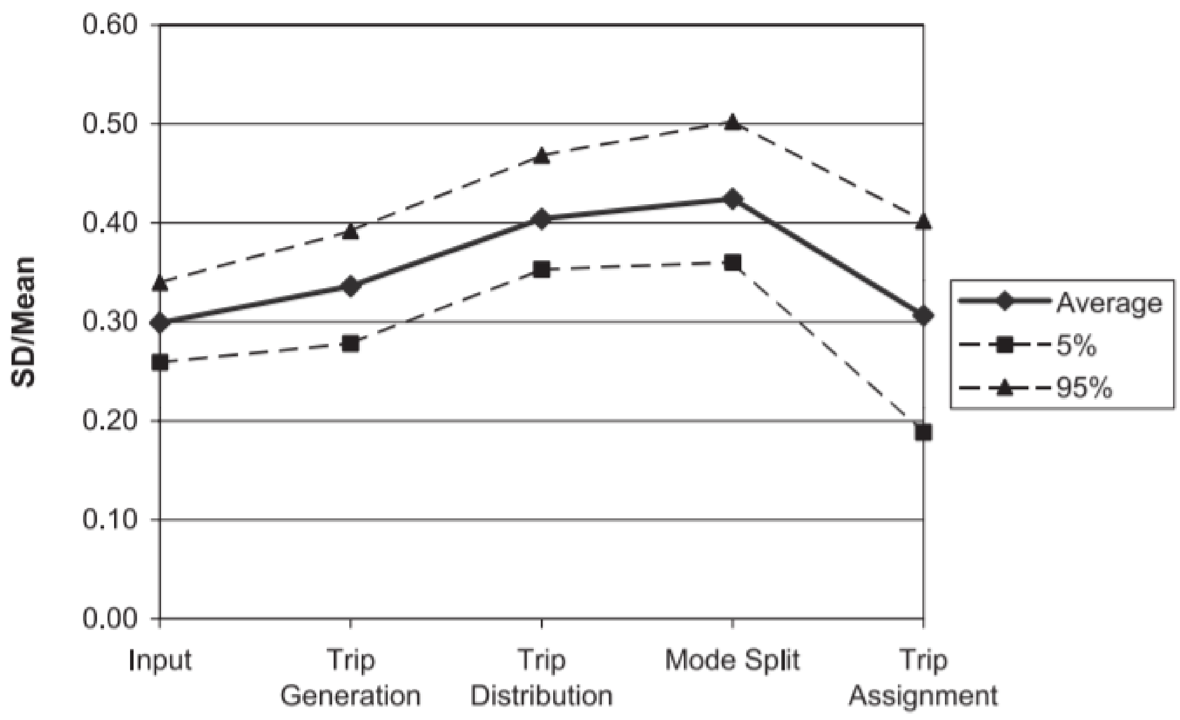


**Figure 7 Results of COV Change Throughout the Four-Step Model by Zhao and Kockelman (2002)**

The literature regarding uncertainty analysis in the context of freight demand modelling is extremely limited with only one paper (Westin et al., 2016) that explicitly studied uncertainty in a (commodity-based) freight demand model. de Jong et al. (2007) examined uncertainty in the Dutch National Model System, which deals with freight transport through external truck O-D matrices as inputs. However, in their study they did not vary the truck O-D matrices, so the effect of an uncertainty source related to freight transport was out of their scope. Westin et al. (2016) authored the only study that directly examined uncertainty in a freight demand model. Their paper used sensitivity analysis by varying the production-consumption (PC) base matrices from -20% to 20% in increments of 10%, for a total of 5 runs, while keeping everything else constant (Westin et al., 2016). The base matrices are the main input of the Swedish national freight model system, SAMGODS (Westin et al., 2016). The results of various outputs were presented graphically and compared to a base scenario (Westin et al., 2016). The authors concluded that model outputs contain uncertainty from the input uncertainty since non-linear responses were observed on the graphs of percent changes between the base scenario and the different simulations (Westin et al., 2016).

Table 6 is a summary of the studies (in chronological order) included in both literature reviews by De Jong et al. (2007) and Rasouli and Timmermans (2012), plus additional studies excluded from those reviews. Over 60 studies were identified, each with varied methodologies tackling input and/or model uncertainty. In general, the additional studies followed the trends discussed above. More obvious is the recent trend towards studying uncertainty in activity-based models.

**Table 6 Summary of the Literature on Uncertainty Analysis in Transportation Demand Models Compiled by (de Jong et al., 2007) and (Rasouli & Timmermans, 2012) with Additional Contributions Found**

| Publication | Model Type | Type of Uncertainty | Variable | Outputs | Methods | Measures |
|---|---|---|---|---|---|---|
| Ashley (1980) | Trip-based passenger model | Input + Model | **Inputs:** income, fuel cost, planning data **Model:** base year matrix, vehicle/mileage elasticities, network speeds, routeing parameter elasticities, | Growth Factors, Future Year Matrix, Traffic flow on specific road links | Random draws from distributions (MC) for inputs and model coefficients | Graph of probability distribution of outputs |
| Lowe et al. (1982) | Trip-based passenger model | Input + Model | **Input:** zonal characteristics, fuel price, and GDP **Model:** route choice coefficient in base year, and route choice elasticity | Link flows | Random draws (10, MC) from distributions for inputs and model coefficients | Percentiles |
| Ben-Akiva and Lerman (1985) | N/A (Discrete choice models) | Model | Transport cost and time coefficients (as an example) | N/A | Analytical formula for model uncertainty in multi-coefficients model | 95% confidence interval |
| De Jong<br><br>-1989 | N/A (car ownership model) | Model | All parameters | Number of households with a car, and km per car per year | Analytical formula for sampling and estimation variance | Standard error |
| Fowkes (1995) | N/A (synthetic utility functions) | Model | Coefficients of modal split including costs, wait time, and in-vehicle time | Mode benefit | Repeated estimation (50) on simulated datasets | Standard error of coefficients and confidence interval of mode benefit |
| Kroes (1996) | N/A | Input + Model | Any deemed critical | Link flows and toll revenues | Repeated model runs assuming all varied variables are independent and assigning subjective probabilities to estimates (low, medium, high) | Standard error and other statistics |

| Publication | Model Type | Type of Uncertainty | Variable | Outputs | Methods | Measures |
|---|---|---|---|---|---|---|
| Brundell-Freij (1997) | N/A (Discrete choice model) | Model | Coefficients of modal split model | N/A (only variation on coefficients was quantified) | Repeated simulation (1500) on estimated datasets for different sample sizes | t-ratios and confidence intervals |
| Leurent (1998) | Trip-based (dual criteria traffic assignment of 4-step) | Input | Value of time, O-D volumes, journey times | Travel times and daily number of cars on a link | Repeated model runs | Standard deviation |
| De Jong et al. (1998) | N/A (update on value of time) | Model | All parameters and value of time | N/A | Jack-knife method to get variances of parameter estimates and draws from multivariate normal distribution (1000, MC) | Standard error |
| Boyce (1999) | N/A (standard aggregate traffic model) | Input + Model | **Input:** several **Model:** elasticities | Change in vehicle-km | Repeated model simulation (10000, MC) drawing from distribution for input variables | Standard error and ration of forecasts |
| Grue (1999) | Trip-based passenger model (4-step) | Model | Parameters for income and quality of transport | Number of cars, number of trips by mode, | Repeated model simulations drawing from distributions for model coefficients | 95% confidence interval |
| Veldhuisen et al. (2000) | Activity-based passenger model (RAMBLAS) | Model (simulation error) | N/A | O-D tables and traffic intensities | Repeated simulations using different MC sets (5) | R-squared, Robinson's agreement measures |
| Brundell-Freij (2000) | Multiple models | Model | Value of time | N/A (only variation on value of time was quantified) | Using MC and bootstrap simulations to run the model specification procedure multiple times (100) | Standard error |
| Pradhan and Kockelman (2002) | LUM[1] data fed into a trip-based passenger model (4-step) | Input + Model | **Input:** population and employment growth rates, household and employment mobility rates **Model:** location choice coefficients, land price coefficient. | **LUM:** Land prices, occupancy rates, occupancy densities **TDM[2]:** VMT[3], VHT[4], selected average link flows | Stratified draws from distributions (factorized design) for inputs to a LUM and are then input to a TDM | COV[5] and p-value of outputs |

| Publication | Model Type | Type of Uncertainty | Variable | Outputs | Methods | Measures |
|---|---|---|---|---|---|---|
| Zhao and Kockelman (2002) | Trip-based passenger model (NTM-4, 4-step) | Input + Model | **Input:** production and attraction rates **Model:** impedance parameter, mode split parameters, volume/delay coefficients, | Link flows | Random draws (100) from multivariate distributions (MC) for inputs and parameters | Standard error of outputs |
| Rodier and Johnston (2002) | Trip-based passenger model (SACMET96, 4-step) | Input | Population and employment, fuel price, household income | Trips, VMT, VHD, multiple types of vehicle emissions | Scenario analysis | Percentage over and underprediction |
| Castiglione et al. (2003) | Activity-based passenger model (microsimulation, San Francisco model) | Model (simulation error) | Random number sequence | Outputs of all sub-models | The sequence of random numbers used to simulate behaviour is changed over 100 runs | Descriptive statistics of outputs and % difference from final mean and . |
| Krishnamurthy and Kockelman (2003) | Trip-based passenger model (UTPP, 4-step) | Input + Model | **Input:** population and employment growth **Model:** all (95) assuming multivariate normal | **Land-Use:** weighted residential and commercial densities **TDM:** VHT, VMT, average link flows, | Random draws (200) (MC) for inputs and parameters | Variance-covariances between parameter, COV and p-value of outputs |
| Armoogum (2003) | Trip-based (demand generation of 4-step) | Input + Model | **Input:** population forecasts **Model:** all parameters | Number of trips and distance travelled | Jack-knifing for parameter recalibration and scenario analysis for input uncertainty | Variance and percentage deviation from reference |
| Boyce and Bright (2003) | - | Input + Model | Several | Revenue | Repeated model simulation, drawing from distributions for input variables and Scenario analysis | Percentiles |
| NCHRP (2003) | N/A (pavement models) | Model | Multiple coefficients | Number of pavement sections | Jack-knife method | Correlation coefficient, standard error |

| Publication | Model Type | Type of Uncertainty | Variable | Outputs | Methods | Measures |
|---|---|---|---|---|---|---|
| Hugosson (2005) | N/A (Discrete choice model) | Model | All logit model parameters | Total and O-D demand by mode, link flows, train lines and value of time (parameter) | Bootstrap sampling, repeated estimation and model application | 95% confidence interval |
| Walker (2005) | Trip-based passenger model with a tour-based step | Model | Auto travel times and sample size | VMT, and number of transit trips | Sensitivity analysis for aggregate error by varying travel times and repetitive simulations (10 each) with different sample size (500, 5k, 50k,500k) for model uncertainty | Percent error |
| Gibb and Bowman (2007) | Activity-based passenger model (SACSIM) | Model (simulation error) | Samples | VHT, O-D Travel times | Repeated simulations (10) with different samples of population | Error bars, standard deviation and evidence of convergence |
| De Jong et al. (2007) | Tour-/activity-based (Dutch National Model System) | Input + Model | **Input:** household disposable income, car ownership, car cost per km, jobs by sector, population by age group, household size, occupation, part/full time employment **Model:** all but fixed coefficients | Total number of tours and km by mode, and selected link flows | Halton draws used to generate numbers for MC (100). Inputs are varied while keeping model parameters constant (40) and vise versa (40) plus the first 10 draw for each are combined (20). | Standard deviations |
| Lawe et al. (2009) | Activity-based passenger model (TRANSIMS) | Model (simulation error) | Seed number | Traffic volumes and average speeds by link | Repeated simulation (5) with different seed numbers | COV |
| Yang and Chen (2009) | Trip-based passenger model (combined travel demand model) | Input + Model | **Input:** several **Model:** route and destination choice, α, γ, parameters, | OD demand, link flow, total travel time, | Stratified random draws (1000) of input variables using LHS for repeated simulations and analytical sensitivity-based analysis for both input and model uncertainty | Derivatives, elasticities, 90% confidence intervals |

| Publication | Model Type | Type of Uncertainty | Variable | Outputs | Methods | Measures |
|---|---|---|---|---|---|---|
| Cools et al. -2011 | Activity-based passenger model (FEATHERS) | Model (simulation error) | N/A | Average daily number of trips per person and average daily distance travelled per person | Repeated simulations (200) for the same 10% fraction of the population | COV |
| Zhang et al. (2011) | N/A (Discrete choice model) | Input + Model | **Input:** demand and supply of travellers **Model:** BPR function parameters (α,β), travelers' value of time, and the coefficient for car operating cost | O-D demand, link flows, WMT, WHT | Random draws (300, MC) varying all uncertainty variables simultaneously | COV |
| Matas et al. (2012) | N/A (Traffic assignment model) | Input + Model | **Input:** GDP, gasoline price, toll prices **Model:** unspecified coefficients | Traffic forecast | Random draws (1000) from assumed distributions assigned to inputs and parameters using bootstrapping. The total uncertainty is estimated from draws that vary all variables, model uncertainty is estimated from draws that held inputs fixed, and a subtraction of the two gives input uncertainty | Confidence intervals |
| Rasouli et al. (Rasouli et al., 2012) | Activity-based passenger model (ALBATROSS) | Model (simulation error) | N/A | Distance travelled and number of trips | Similar to Cools et al. (2011) | COV and confidence intervals |
| Yang and Chen (2013) | Trip-based passenger model (combined travel demand model) | Input + Model | **Input:** travel cost and number of potential travellers **Model:** attractiveness, route, mode, destination, travel time, α, and γ parameters | OD demand, link flow, total travel time, total vehicle miles | Analytical sensitivity-based analysis for both input and model uncertainty | Differences, 90% confidence intervals, and correlations |

| Publication | Model Type | Type of Uncertainty | Variable | Outputs | Methods | Measures |
|---|---|---|---|---|---|---|
| Adler et al. (2014) | Trip-based passenger model with corridor macroscopic simulation | Input | Value of time per hour, economy, toll rate/mile | Daily one-way trips using I-4 Express Lanes | A response surface methodology approach consisting of a R:1/3 $3^3$ fractional factorial design with distribution of the inputs estimated based on data and distribution of the output estimated running a MC simulation on the surface model | Graphical distribution of output |
| Bekhor et al. (2014) | Activity-based passenger model | Model (simulation and sampling error) | Sample size | VHT | Repeated simulation similar to Cools et al. (Cools et al., 2011) | Deviation from average |
| Bao et al. (2015) | Activity-based passenger model (FEATHERS) | Model (simulation error) | N/A | Average daily activities per person, average daily trips per person, average daily distance travelled per person | Repeated simulation (100) to find stable average based on number of runs. Similar to (Cools et al., 2011) | Graphs of percentiles vs. number of runs |
| Bao et al. (2016) | Activity-based passenger model (FEATHERS) | Input | Multiple variables | Choice frequency | Once-at-a-time approach to quantify output distribution by selected varying input while keeping others as observed. Quasi-random draws (5120, Sobol method) while varying inputs. | Sensitivity measures (impact condition, coefficient of monotonicity |

| Publication | Model Type | Type of Uncertainty | Variable | Outputs | Methods | Measures |
|---|---|---|---|---|---|---|
| Copperman et al. (2016) | Trip-based passenger model (BPM-V3) | Input | Multiple risk input variables | High Speed Rail Revenue | A response surface methodology approach consisting of a 3-level fractional factorial design runs (81,plus 27), probabilistic design runs (27), and extreme scenario runs (5) with distribution of the inputs estimated based on data and distribution of the output estimated running a MC simulation on the surface model | Graphical distribution of output |
| Petrik et al. (2016) | N/A (Discrete choice model) | Input + Model | **Input:** socio-economic and mode shift inputs<br>**Model:** all parameters | Mode shift | Re-estimation of model using bootstrap (10000)<br>Input uncertainty was quantified by generating a synthetic population, varying socio economic, mode-specific, and combined inputs through a MC (10000 each time) | Standard deviation as percentage of the mean for mode shift |
| Westin et al. (2016) | Commodity-based freight model (SAMGODS) | Input | PC matrices | Tonne-km, vehicle-km per mode (road, rail, sea), consolidation levels, order cost, holding cost, transport cost, total cost | The PC matrices are varied from -20% to 20% in 10% increments while keeping everything else is constant during repeated simulations (5) | Percent change from base scenario |

| Publication | Model Type | Type of Uncertainty | Variable | Outputs | Methods | Measures |
| --- | --- | --- | --- | --- | --- | --- |
| Petrik et al. (2018) | Activity-based passenger model | Model (parameter, simulation error, sampling error) | Important parameters, sample size | VKT, PKT, Number of trips, Number of tours, different type of tour mode shares | Sensitivity analysis using a meta-model determined important parameters to use in a repeated simulation (500) with LHS draws to assess parameter uncertainty. Simulation error was done similar to Cools et al. (Cools et al., 2011). Sampling error was done by repeated simulation with different sample sizes. | Standard deviation and COV |
| Zhuge et al. (2019) | Activity-based passenger model (MATSim) | Model (parameter) | Population scaling factor, number of iterations, time step size, time mutation rate, performing utility | Plan score, travel distance, average V/C ratio, travel speed, standard deviation of V/C ratio | Sensitivity analysis to identify influential parameters then once-at-a-time local sensitivity analysis to identified parameters | Graphical once-at-a-time results with standard deviations |

[1] Land-use Model (LUM)
[2] Travel Demand Model (TDM)
[3] Vehicle Miles Travelled (VMT)
[4] Vehicle Hours Travelled (VHT)
[5] Coefficient of Variation (COV)
[6] Urban Transportation Planning Package's (UTPP)

## 2.4. Gaps in the Literature and Conclusions

For the remainder of this thesis, the terminology used to describe and categorize different freight demand models is based on the unit of reference for demand generation. Although there was disagreement in the literature regarding the correct terminology, this categorization was referenced and used in the other two systems identified (spatial scope and US Class System), making it commonly used. Additionally, it is easy to quickly identify general characteristics of the examined models when referring to them by using their reference units. For example, trip-based models need the least computation effort, followed by commodity-based models, and trailed by agent-based models. General characteristics are not readily apparent when defining models using spatial scope since both long or short distance models may require a large or small computational effort depending on their level of detail. On the other hand, the US Class System breaks down the models into more categories that sometimes makes discerning specific characteristics or patterns confusing. Moreover, the unit of reference for demand generation is widely quoted in most of the studies examined in this literature review suggesting that most researchers and practitioners are acquainted with the terminology.

The most widely used type of freight demand model in practice is the commodity-based model. This was less apparent in the Canadian review than in the US review. However, the Canadian state-of-practice review was not comprehensive due to the limited information available publicly. It is also commonly known that freight modelling is more widely used in the US than in Canada in practice. For example, the FAF has been around for a long time in the US (it has been developed up to its fifth version) and it is capable of forecasting and assignment unlike its Canadian counterpart (CFAF), which is a newer and less developed tool. Moreover, state-wide commodity-based models are more common in the US due to its more complex geography. Canada exhibits simpler inter-provincial freight patterns because the provinces run east to west (no interior states) with fewer major highways. Thus, smaller-scale models (e.g., within cities or metropolitan areas) that are trip-based, due to the higher availability of vehicle trip data, are more frequently developed in Canada. It is safe to conclude that commodity-based freight demand models are more widely used when looking at both countries in aggregate. However, it is also important to note that multiple authors pointed at the trend towards activity-based modelling in industry (Chow et al., 2010; Liedtke & Schepperle, 2004; National Cooperative Highway Research Program, 2008; Nuzzolo et al., 2013; Wisetjindawat et al., 2012).

There are two important gaps in the literature regarding uncertainty analysis in freight demand models. First, there is a lack of a formal approach to studying uncertainty specific to freight demand models. As mentioned before, only one study has dealt with this topic and it used a simple sensitivity analysis approach (Westin et al., 2016). A more methodical approach is needed using the best practices identified in the review. Second, there is no analysis studying the propagation of uncertainty through successive sub-models in freight demand models. In Section 2.1.2, commodity-based models are explained to generally be composed of a set of successive sub-models. Thus, a formal study of the propagation of uncertainty through a commodity-based freight demand model, akin to the analysis that Zhao and Kockelman (2002) performed on a passenger demand model, is needed.

Other gaps in the uncertainty analysis literature that have been somewhat studied but need a more substantial research effort include the following:

- Using other more systematic variations instead of Monte Carlo simulation such as factorial designs, probabilistic designs, etc.
- Estimating the distribution of the parameters and/or inputs as supposed to making assumptions.
- If distributions are assumed, using types other than univariate normal or multivariate normal distribution to compare the impact of those assumptions.
- Using a more educated approach to selecting variables to vary in the repeated simulations (i.e., which variables affect the outputs the most based on practical/outside experience and knowledge).

# Chapter 3. Methodology

The literature review found that there is a lack of a formal approach to studying uncertainty specific to freight demand models, as well as the absence of any study of uncertainty propagation through successive sub-models in freight demand models. To this end, a framework to study the uncertainty due to inputs on the outputs of commodity-based freight demand models is developed.

This section first introduces the case study model to which the framework is applied. The model of the case study was developed by Bachmann (2017) and Jahangiriesmaili et al. (2018) and it is used to analyze the effects of the Comprehensive and Progressive Agreement for Trans-Pacific Partnership free trade agreement on Canada's trade infrastructure. This model is subsequently referred to as "the model" and is introduced later in the section. Then, the methodology of a general framework that can be used to assess input uncertainty in any commodity-based freight demand model is presented along with the details of the application of the framework to the case study model. The framework is developed following the best practices learned through the review of the literature.

## 3.1. Case Study Model

The model used in the case study was developed to study the effects of FTAs on Canada's domestic trade infrastructure. The model was first developed by Bachmann (2017) who extended a typical CGE simulation of CETA through the estimation of high-level supply chain characteristics. Later, Jahangiriesmaili et al. (2018) expanded this work to assess the potential impact of CETA on Canada's transportation network by estimating before-and-after origin-destination trade flows, mode shares, and transportation flows. The result of these efforts was a commodity-based freight demand model, capable of assessing the effects of FTAs on the transportation of commodities throughout Canada.

This research is extending earlier work (Bachmann, 2017; Jahangiriesmaili et al., 2018) to analyze the effects of the CPTPP, signed in 2018, using CGE forecasts for 2015, 2035, and 2035 after implementing CPTPP policy shocks (Dade et al., 2017). Through this application, the CGE forecasts developed in Dade et al. (2017) are used to create the base case of this thesis' case study. In Chapter 4, the results of this base case are compared to the results of the repeated simulation.

The developed freight model is a data-driven commodity-based model of the aggregate-disaggregate-aggregate (ADA) freight model described by Ben-Akiva and De Jong (2013). It follows a modified version of the traditional four-step approach. Figure 8 shows a summary of the model alongside a typical description of a four-step freight demand model. A major deviation from the traditional four-step approach is the lack of parameter estimation. For each step, a share is empirically calculated using CBSA, CFAF, or the International Trade Division of Statistics Canada datasets. This was done to study only input uncertainty as there is no model estimation and therefore there is no model uncertainty introduced.

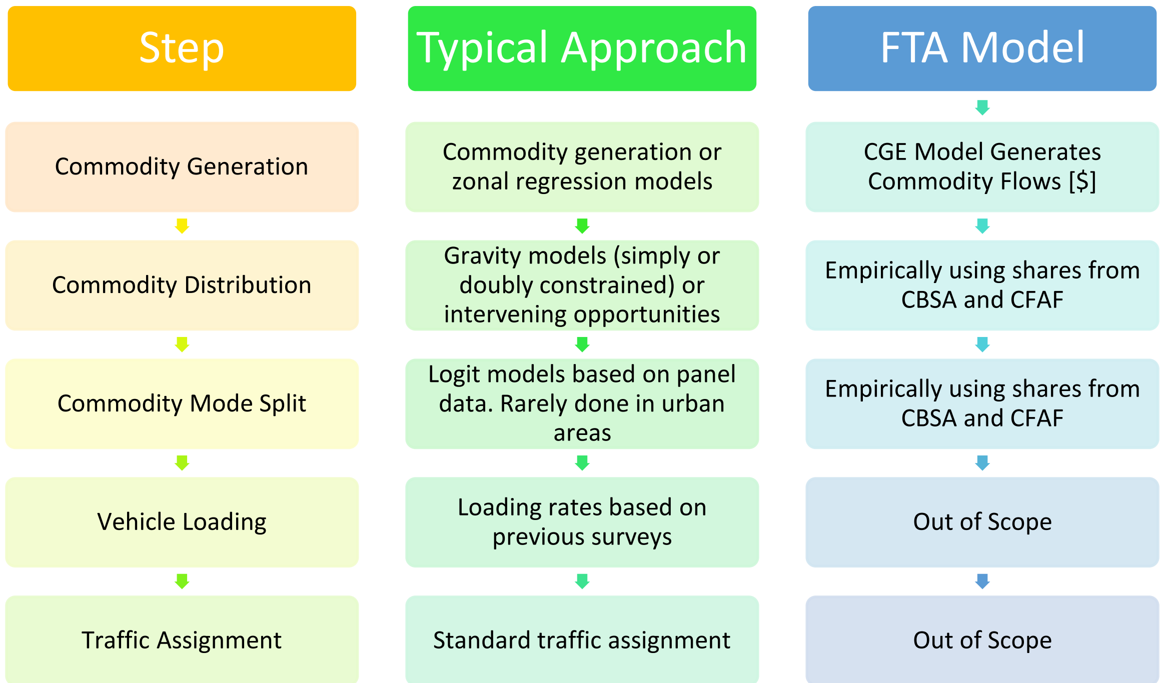


**Figure 8 Case Study Model Comparison**

Figure 9 shows the ADA modelling process. The ADA approach intends to overcome two major drawbacks of most freight transport models: 1) the lack of important aspects of logistics decision-making and 2) the assumption of zone to zone (aggregate level) mode optimization (Ben-Akiva & de Jong, 2013). To achieve this, the generation of trade flows or production-consumption flows and assignment to networks is done in an aggregate way, but the logistic decisions are simulated at the level of individual firm-to-firm pairings (Ben-Akiva & de Jong, 2013). In the disaggregate portion of these models, logistics models can take into account shipment size and transport chain choice by minimizing total logistics costs (Ben-Akiva & de Jong, 2013). The difference between the ADA framework and the model used in this research is that the logistic decisions are derived empirically in the latter. In the ADA framework, the decisions are typically modelled using random utility maximization derived from behavioural choice theory.

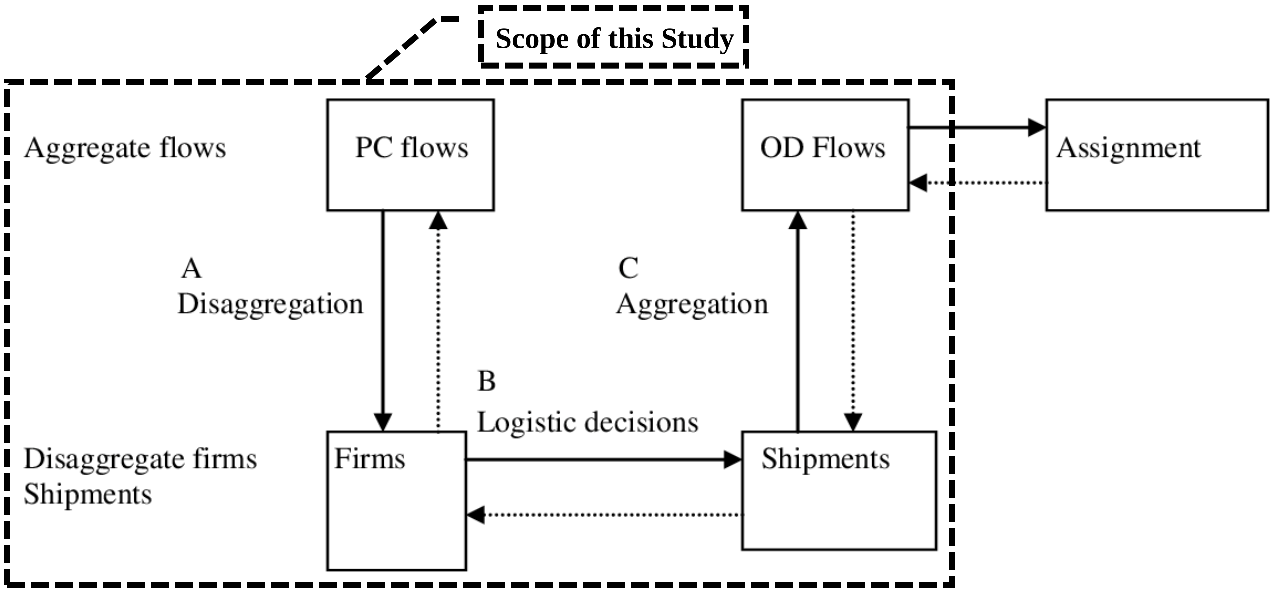


**Figure 9 ADA Modelling Schematic (Ben-Akiva & de Jong, 2013)**

The resulting commodity-based freight demand model is depicted in Figure 10. In summary, the model is composed of four steps: a CGE economic model, and the following three steps are the sub-models that make up the freight model:

1. A sub-model is used to estimate the high-level supply chain characteristics of each trade flow, including subnational region of origin/destination, subnational region of entry/exit, international transport mode, and port of clearance using CBSA export records (i.e., aggregate to disaggregate trade flows [$]).
2. A sub-model is used to transform trade flows from value ($) to weight (kg) using value-weight ratios obtained by linking data from the International Trade Division of Statistics Canada to the CBSA export records.
3. A sub-model is used to estimate the domestic mode splits in tonnes using data from the CFAF assembled by Statistics Canada. These flows can then be aggregated into O-D flows.

The following subsections expand on the explanation of each step focusing on export flows, as export data are used for the analysis of uncertainty.

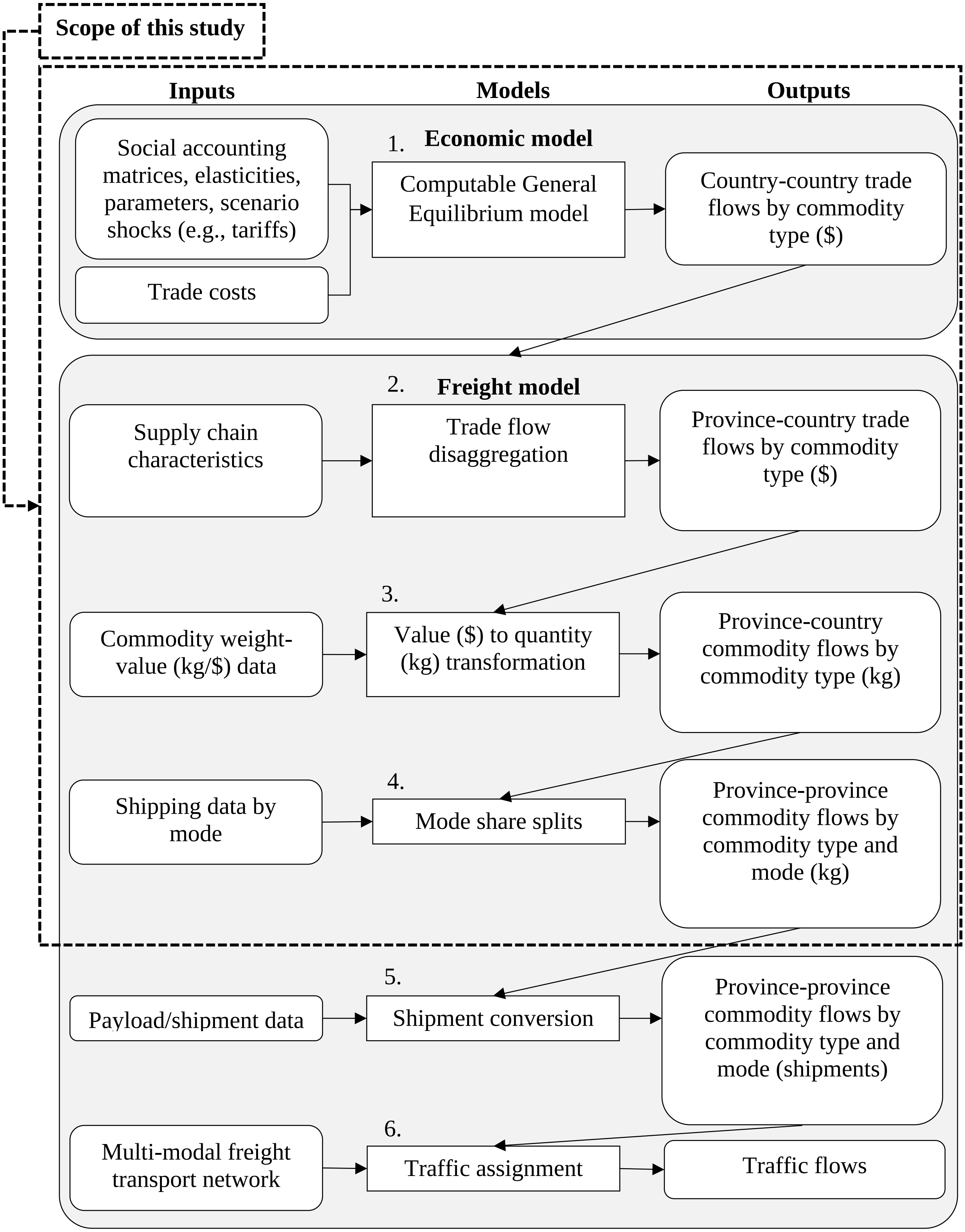


**Figure 10 Modelling Framework and Study Scope**

The spatial scope of the model can be divided into two. First the economic model (see Section 3.1.1) focuses on exports and imports to/from Canada to/from another 39 economies representing all the other regions of the world (see Table 9 for a full breakdown of these economies). Second, the freight model allocates those commodities flows to the Canadian domestic trade network. The figure below shows the provinces and territories (later referred to as subnational regions), the main gateways (defined more in detail in Section 4.2.1), and their interactions with the rest of the world economies.

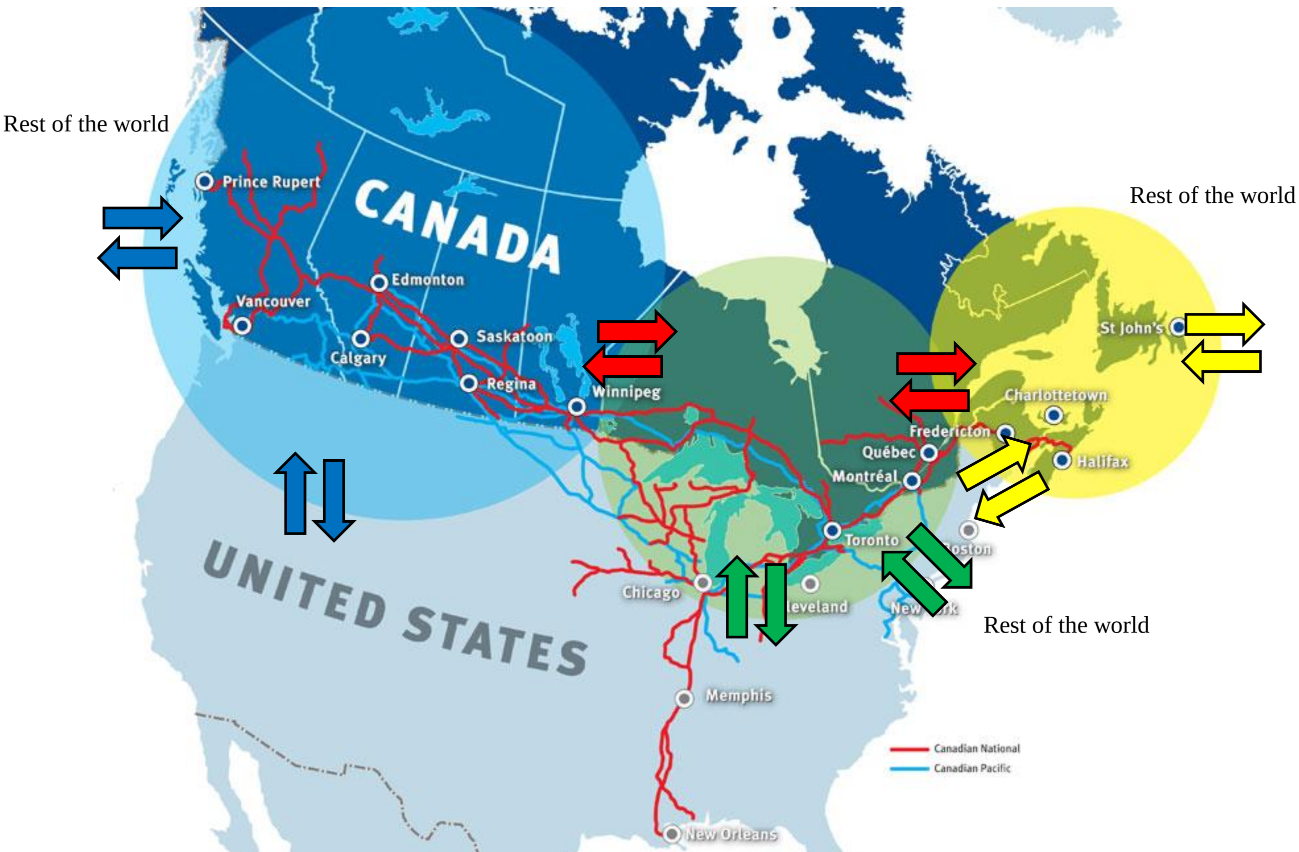


**Figure 11 Representation of Canada's Domestic Trade Network**

### 3.1.1. Economic Model

The first step is a CGE economic model. CGE models are typically used to simulate the changes to international trade flows caused by the enforcement of an FTA (Bachmann, 2017). CGE models are a system of equations that represent macroeconomic constraints on the economy and individual microeconomic interactions between parts of the economy. An initial set of equilibrium commodity quantities and prices are specified for a particular economy and year. Then, an exogenous variable is changed (e.g., changes brought upon by an FTA such as tariff reductions etc.). Finally, the model is re-solved for new equilibrium commodity quantities and prices. Burfisher (2017) provides an excellent introduction to CGE models that includes the theory and applications regarding FTAs (Bachmann, 2017).

### 3.1.2. Freight Model

#### 3.1.2.1. High Level Supply Chain Characteristics

High-level supply chain characteristics (e.g., subnational region of origin/destination, subnational region of exit/entry, international transportation mode, and port of clearance) are modelled after the effects of the CPTPP on international exports (Bachmann, 2017). Equation 1 shows the first sub-model of the freight model (second step of the general model) which disaggregates the international (country-to-country) trade flows into province-to-country trade flows to estimate their high-level supply chain characteristics. Shares for each characteristic combination can be determined using export data. Then, these are applied to the international trade flows as per the equation below.

$$z_{i,j,k,l,m,n} = s_{i,j,k,l,m,n} \times z_{i,l} \tag{1}$$

where $z_{i,j,k,l,m,n}$ is the trade flow ($) (disaggregated) of commodity *i* produced in subnational region *j* exported by subnational region *k* to country *l* by international mode *m* through port of clearance *n*. $s_{i,j,k,l,m,n}$ is the international export share of commodity *i* exported to country *l* that is produced in subnational region *j* exported by subnational region *k* by international mode *m* through port of clearance *n*, determined from initial shares in the export trade data. $z_{i,l}$ is the international trade flow ($) of commodity *i* to country *l*, from the CGE forecasts by Dade et al. (2017).

It is assumed that an FTA does not affect the existing subnational supply chains in order to use the existing shares to disaggregate the trade flows. For example, the share of international exports that exit through port of clearance *n* remains unchanged after the FTA is introduced. The original purpose of this model was to identify areas in the transportation network that exhibit a large change in commodity flows and thus congestion may occur. The supply chains may shift in these areas of high congestion although this is not captured by the model.

#### 3.1.2.2. Value to Quantity Transformation

Monetary values are converted into physical quantities to capture the physical transportation impacts of commodity trade flows. Value-weight ratios ($/tonne) can be determined using trade data. The following equation depicts the aforementioned conversion:

$$t_{i,j,k,l,m,n} = \frac{z_{i,j,k,l,m,n}}{w_{i,j,k,l,m,n}} \tag{2}$$

where $t_{i,j,k,l,m,n}$ is the trade flow (tonnes) of commodity *i* produced in subnational region *j* exported by subnational region *k* to country *l* by international mode *m* through port of clearance *n*. $w_{i,j,k,l,m,n}$ is the value-weight ratio ($/tonnes) for shipments of commodity *i* produced in subnational region *j* exported by subnational region *k* to country *l* by international mode *m* through port of clearance *n*.

Value-weight ratios are measured in initial prices, meaning that the forecasted trade flows in monetary units ($z_{i,l}$) must also be measured in initial prices or any price increase in the policy replacement scenario will inflate the tonnage in Equation 2. Measuring a change in initial prices is referred to as volume change in CGE modelling. On the other hand, value change is measured in final prices.

Some of the subscripts in $w_{i,j,k,l,m,n}$ can be dropped if data are limited. However, they are useful in distinguishing supply-chain characteristics that can affect value-weight ratios. For example, a study using a model specific to marine analysis found that exports to less developed countries are heavier than to developed countries and that expensive goods tend to be transported further away (Luis et al., 2014).

#### 3.1.2.3. Domestic Mode Splits

The last sub-model of the fright model (fourth step) estimates domestic flows using observed freight shipments in Canadian transportation survey data and aggregates them by provincial O-D pair:

$$t_{j,k,d} = \sum_i \left( s_{i,j,k,d} \times \sum_l \sum_m \sum_n t_{i,j,k,l,m,n} \right) \tag{3}$$

where $t_{j,k,d}$ is the total trade flows (tonnes) shipped from subnational region $j$ to subnational region $k$ by domestic mode $d$. $s_{i,j,k,d}$ is the share of commodity $i$ shipped from subnational region $j$ to subnational region $k$ by domestic mode $d$.

### 3.2. Case study - CPTPP Model Data

This section describes the data used for the CPTPP base analysis and all the available data for each step of the model. A summary of the datasets used in the model is shown in Table 7.

**Table 7 CPTPP Model Data Summary**

| Data Source | Description | Model Usage |
|---|---|---|
| **GTAP**[1] | Describes bilateral trade partners, production, consumption and intermediate use of commodities and services. | CGE export forecasts (economic model). |
| **CBSA** | Export data (2010-2015) including Harmonized Systems code, SCTG[2] code, provinces of origin and exit, country of destination, international mode of transport, and port of clearance. | Supply chain characteristics (first sub-model) and value-weight ratios (second sub-model). |
| **International Trade Division of Statistics Canada** | Total value ($) and weight (kg) of exports and imports by SCTG code (2008). | Value-weight ratios (second sub-model). |
| **CFAF** | Integrated dataset (2011-2017) of freight flows across Canada including estimated tonnage, value, and tonne-kilometers, origin and destination provinces, commodity types, and mode. | Domestic mode split (third sub-model). |

[1]Global Trade Analysis Project

#### 3.2.1.1. Economic Model Data

The model used for the economic forecasts utilized as inputs for the successive freight model is a dynamic version of the GTAP CGE model (Dade et al., 2017). CPTPP policy shocks considered included non-tariffs barriers in goods and services and foreign direct investment (FDI), liberalization commitments for tariffs, and effects of rule of origin on preference utilization. FDI is simulated by introducing a foreign-owned representative firm into each GTAP region-sector. The simulation is done using the GTAP V9 database with a base year of 2011, the CPTPP is assumed to enter into force on January 1, 2018, and it covers 33 sectors (see Table 8) and 40 economies (see Table 9). The sector market is classified using the GTAP Sector Classification (GSC2). The GTAP database is simulated forward to the year 2035. Then, the same simulation is ran with CPTPP policy shocks for comparisons. For a detail report on this simulation and its findings refer to Dade et al. (2017).

**Table 8 Sectors in CGE model (Dade et al., 2017)**

| Agriculture and Food | Forestry, Fishing, Mining | Industry and Manufacturing | Services |
|---|---|---|---|
| Rice | Forestry | Textiles and Apparel | Construction |
| Wheat and Cereals Fruit and Vegetables | Fishing | Leather Products | Trade |
| Oil Seeds and Vegetable Oils | Fossil Fuels | Chemicals, Rubber, and Plastics | Transport |
| Sugar | Mineral Products | Metals and Metal Products | Communication |
| Dairy | | Automotive | Financial Services |
| Beef | | Transport Equipment | Business Services |
| Pork and Poultry | | Electronic Equipment | Recreation |
| Other Agriculture | | Machinery and Equipment | Other Services |
| Food Products | | Other Manufactures | |
| Beverages and Tobacco | | | |

**Table 9 Economies in CGE Model (Dade et al., 2017)**

| CPTPP[1] | Other RCEP[2] | TTIP[3]/Other TISA[4] | TFTA[5] and ROW[6] |
|---|---|---|---|
| Australia | Indonesia | EU28[9] | Ethiopia |
| Canada | Philippines | Norway | Kenya |
| Chile | Thailand | Switzerland | Mozambique |
| Japan | Rest of Southeast Asia[8] | Other EFTA[10] (Iceland and Liechtenstein) | Tanzania |
| Malaysia | China | Israel | Uganda |
| Mexico | Korea | Pakistan | Rwanda |
| New Zealand | India | Turkey | Rest of East Africa |
| Peru | | Hong Kong | SACU[11] |
| Singapore | | Taiwan | Other TFTA[5] |
| U.S.[7] | | Colombia | ROW[6] |
| Vietnam | | Central America (Costa Rica and Panama) | |
| | | Other South America (Paraguay and Uruguay) | |

[1]Comprehensive and Progressive Trans-Pacific Partnership
[2]Regional Comprehensive Economic Partnership
[3]Transatlantic Trade and Investment Partnership
[4]Trade and Services Agreement
[5]Tripartite Free Trade Area
[6]Rest of World
[7]United States of America
[8]Brunei (a CPTPP country) is part of Rest of Southeast Asia
[9]European Union
[10]European Free Trade Association
[11]South African Customs Union

Lastly, monetary manipulations of the GTAP trade flows were needed as well. First, the CGE trade flows, in 2011 US dollars (USD), were converted to Canadian dollars (CAD) using the 2011 exchange rate of 1 USD to approximately 0.99 CAD. Second, the CAD values were adjusted for inflation to match the years of the other datasets. Consumer Price Index (CPI) was used to adjust the units of the CGE forecasts, after their conversion to CAD. For example, in the base case, the CGE forecasts were multiplied by a 2015 CPI of 126.6 and divided by a 2011 CPI of 119.9 (base year 2002=100) to bring the monetary year of the trade values (2011) forward and match the year for the CBSA data (2015).

Using this data, the resulting international trade flows ($z_{i,l}$) are multidimensional. The number of sector aggregations or commodities ($i$) is 33 and the number of countries or international regional aggregations ($l$) is 39 (excluding Canada). This creates 72 distinct international supply chains of exports.

#### 3.2.1.2. Freight Model Data

#### 3.2.1.3. Data for High Level Supply Chain Characteristics

The shares in Equation 1 ($s_{i,j,k,l,m,n}$) are empirically calculated using CBSA export data. The data were provided to Transport Canada from Statistics Canada (Bachmann, 2017). There are six years available of export data between 2010-2015. The export data include several attributes: Harmonized System (HS) codes for sectors, province of exit ($k$), country of destination ($l$), international mode of transport ($m$), and port of clearance ($n$). The export data are in monetary units. For example, for the base case, the 2015 data were used thus the units of the trade flows were 2015 Canadian dollars (2015 CAD).

Correspondence tables of different sector classification systems were used in order to pair the appropriate sectors between the calculated shares ($s_{i,j,k,l,m,n}$) and the results from the CGE economic model ($z_{i,l}$) in Equation 1. This is necessary since the shares ($s_{i,j,k,l,m,n}$) use the HS sector classification system and the forecasted trade flows ($z_{i,l}$) use GSC2. There are correspondence tables provided by GTAP between GSC2 and Central Product Classification (CPC) and between GSC2 and International Standard Industrial Classification (ISIC). Both concordance tables are needed because GSC2 includes both commodities and industries. Correspondence tables between HS-CPC and CPC-ISIC are also available through the United States Statistical Division. Figure 12 summarizes the procedure to assign a GSC2 code to the shares ($s_{i,j,k,l,m,n}$) using the concordance tables.

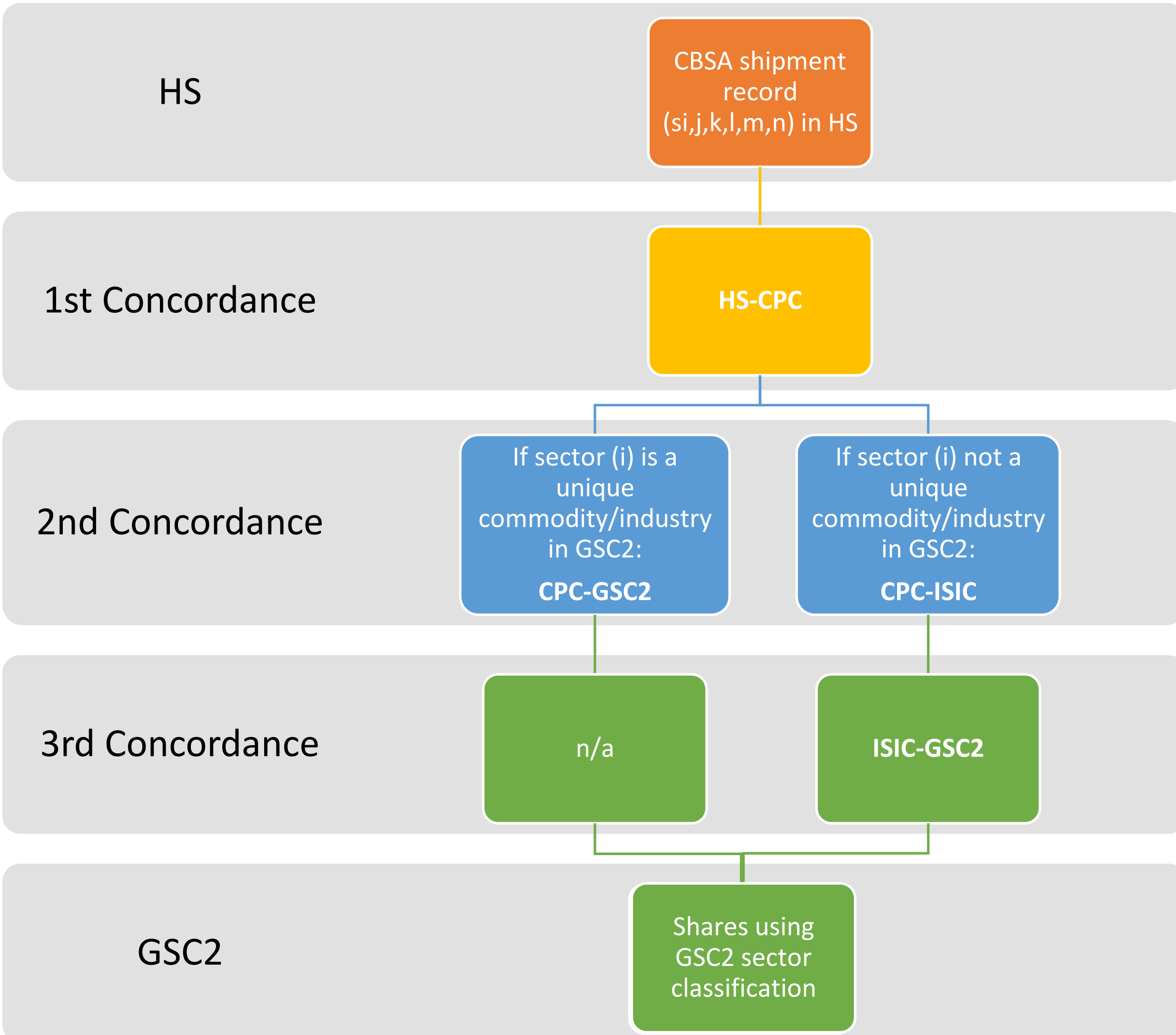


**Figure 12 Procedure to Assign GSC2 Code to CBSA Shares**

This procedure was previously validated by Bachmann (2017) for 2011 export trade flows. It is an aggregation scheme since the CBSA data classification system (HS) is coded at a higher sectorial detail than the GSC2 forecasts. Bachmann (2017) compared the CBSA aggregated trade flows (i.e., the raw data before they are converted into shares) to the GTAP trade flows for 2011. Correlation between the two sets mean approximately 0.96 and ranged from 0.89 (exports to Middle East and North Africa) to 0.99 (exports to rest of Europe) for all regions in the model. This indicates very good consistency between the CBSA trade flows aggregated by GSC2 code and the CGE forecasts for 2011.

Using this data, the resulting disaggregated trade flows ($z_{i,j,k,l,m,n}$) are multidimensional. The number of sector aggregations or commodities ($i$) is 33, the number of subnational regions ($j$,$k$) are 11 each (including all provinces with the territories being aggregated into one representative region), the number of countries or international regional aggregations ($l$) is 39 excluding Canada, the number of international modes ($m$) is 5 (air, water, road, rail, other), and the number of ports of clearance ($n$) is 246 (see Figure 22 for their locations). This totals approximately 191.5 million distinct supply chains of exports.

#### 3.2.1.4. Data for Value to Quantity Transformation

The International Trade Division of Statistics Canada provided value-weight data for the year 2008. The data included the total value (2008 CAD) and weight (kg) of exports and imports by six-digit Standard Classification of Transported Goods (SCTG) commodity code. For each SCTG commodity, a value-weight (2008CAD/kg) ratio is calculated and then linked to the CBSA data (2010-2015 CAD) in order to create the value-weight ratios ($w_{i,j,k,l,m,n}$) unique to each supply chain that are used in Equation 2.

In this case, additional momentary manipulations are needed as well since the CBSA data and the International Trade Division of Statistics data have units in CAD for different years. For example, in the base case, the 2015 CBSA data were multiplied by a 2008 CPI of 114.1 and divided by a 2015 CPI of 126.6 (base year 2002 = 100) to match the year of the value-weight ratios (2008). The 2008 CAD units cancel out during final value-weight ratio ($w_{i,j,k,l,m,n}$) calculations.

Using this data, the resulting disaggregated trade flows in tonnages ($t_{i,j,k,l,m,n}$) are multidimensional. The number of supply chains is the same as the desegrated trade flows in monetary values ($z_{i,j,k,l,m,n}$) with a total of approximately 191.5 million distinct supply chains of exports.

#### 3.2.1.5. Data for Domestic Mode Splits

The Canadian Freight Analysis Framework is maintained by Statistics Canada and contains domestic freight data for the years 2011 to 2017. Attributes of the database include estimated tonnage, value, tonne-kilometers, O-D provinces, 12 commodity types (aggregations of SCTG), and three modes (air, rail and truck). The microdata are not yet available at the time of this study, thus the publicly available aggregated data were used to calculate the domestic mode shares for each of the 12 commodities between province pairs ($s_{i,j,k,d}$) used as inputs for Equation 3. The SCTG aggregations are linked to HS codes, using a correspondence table, which are then linked to the GSC2 codes as previously explained.

Using this data, the resulting domestic trade flows in tonnages ($t_{j,k,d}$) are multidimensional. The number of subnational regions ($j$,$k$) are 11 each, and the number of domestic modes ($d$) is 2 (truck and rail). This totals 242 distinct domestic supply chains.

## 3.3. Framework

The framework presented in Figure 13 is a formalized approach proposed to study the uncertainty due to inputs on outputs of commodity-based freight demand models based on the literature review found in Section 2.3. An explanation of each step of the framework is provided below. The literature has shown that input uncertainty is often a greater contributor to uncertainty of the outputs than model uncertainty (de Jong et al., 2007). Additionally, the same or similar datasets are used as inputs for multiple commodity-based freight demand models, whereas uncertainty due to model specification/calibration is more specific to the development of each model. For these reasons, the framework below was developed to analyze uncertainty in the outputs of freight demand models due to uncertainty in the inputs. This method can be used to assess the uncertainty of the model due to one or multiple inputs depending on the identification step.

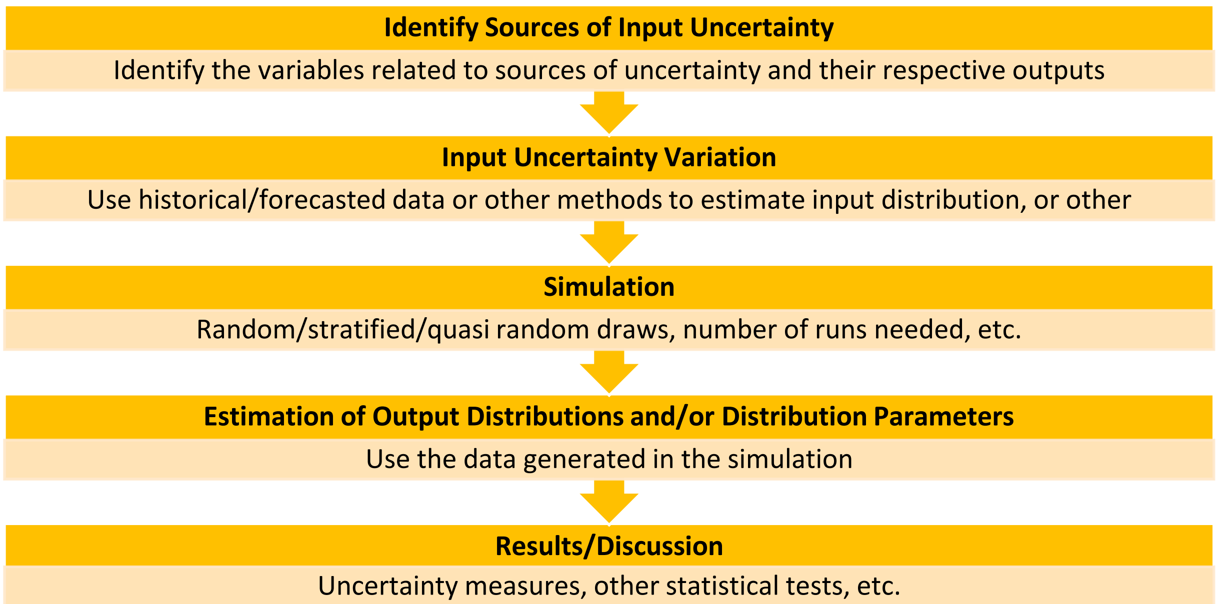


**Figure 13 Framework for the Analysis of Uncertainty in Commodity-Based Freight Demand Models**

The case study model was used to assess the effects of the CPTPP on Canada's trade infrastructure by using a specific set of years and other variables to develop the parameters of the model. This is referred to as the base case in this thesis. As seen in Section 3.2, there is a range of data available to use in the calculation of various inputs to the model. The major question then becomes: how different are the results of the same analysis after introducing variation on certain inputs when compared to the base case? Note that this framework is only applied to the freight model (as described in Section 3.1.2) and not the economic model (i.e., the economic forecast is fixed).

First, a formal introduction of the base case is needed. The economic model results are one of the inputs to the first sub-model of the freight demand model (recall Figure 10). They consist of forecasted 2015 trade flows, forecasted 2035 trade flows, and forecasted 2035 trade flows after CPTPP policy shocks all in monetary units with a base year of 2011. The other inputs of the first freight sub-model are the supply chain shares ($s_{i,j,k,l,m,n}$), which in the base case are calculated using 2015 CBSA (most recent) data. Next, the base case inputs for the second sub-model, the value-weight ratios ($w_{i,j,k,l,m,n}$), are calculated using value-weight data with sectors classified using 5-digit SCTG codes (most disaggregated) in combination with 2015 CBSA data. Finally, the inputs for the third sub-model, the domestic mode shares ($s_{i,j,k,d}$) are calculated using 2015 CFAF data in the base case (matching the CBSA data).

The rest of this section is divided as per the framework presented in Figure 13. Each subsection describes the general aspects of each step and its application to the case study.

### 3.3.1. Step 1: Identify Sources of Input Uncertainty

As explained in Section 2.3.1, input uncertainty refers to the error in the data used as inputs for the transportation demand model (de Jong et al., 2007; Rasouli & Timmermans, 2012). Examples of such sources of uncertainty are biased surveys, incomplete datasets, varying commodity and industry classifications, varying sector classifications, error in economic forecasts (e.g., a CGE model feeding forecasts into a freight demand model), etc.

In this step, the goal is to identify all sources of error in the inputs and their respective outputs. First, identify all the inputs that have uncertainty associated with them. Transportation models are sometimes extensive and may have countless input variables that are uncertain. In those cases, it is important to identify which inputs are more critical for the analysis that is intended to be aided by the model. There are multiple ways to analyze which variables have a greater effect on certain model outputs. For example, a simple sensitivity test can be used by varying the inputs over a specified range one at the time and seeing how the desired output is affected. This can be measured in percent change relative to the original output value. A high percent change seen in the output caused by varying a specific input means that this input has a high effect on the output of the model. Similarly, if the assumption of normality is made, then multiple linear regression can also be used to identify which variables have a greater effect on a desired output.

Second, identify all the outputs that may be affected by the sources of input uncertainty directly and as a result of uncertainty propagation through successive models. Commodity-based models often follow a version of the traditional four-step model approach. Therefore, it is necessary to identify the sources of uncertainty in the inputs at each step or sub-model. If a particular input is related to a particular output alone, then these relations should be noted in order to analyze their isolated effects. This way, the propagation through successive sub-models can be compared to the uncertainty found at a particular step due to a particular input.

Third, identify the type of data available for the chosen inputs. Identifying the available data aids in the completion of the next step, which is estimating input uncertainty distributions. There can be estimations of distributions and distribution parameters in the literature for some inputs. Similarly, if the inputs are the results of other modelling techniques (e.g., economic, land-use), then the variables may be modelled as probability distributions with the mean value used as inputs in the freight demand model. On the other hand, inputs may have multiple years of historical data. Depending on the model, historical data can be used directly to vary the identified inputs.

The case study freight model is simple in terms of input parameters. Essentially, for each equation there is one input that may be a source of new uncertainty and one input that carries the uncertainty of the previous sub-model. For the first sub-model (Equation 1) the input is the supply chain shares ($s_{i,j,k,l,m,n}$). The CGE forecasts are also inputs for the first sub-model, but they are out of the scope of this study since this study focuses on the freight model, not the economic model. For the second sub-model (Equation 2) the input is the value-weight ratios ($w_{i,j,k,l,m,n}$) and the source that carries over the previous sub-model's uncertainty is the disaggregated trade flows in monetary values ($z_{i,j,k,l,m,n}$). For the last sub-model (Equation 3) the input is the domestic mode shares ($s_{i,j,k,d}$) and the source that carries over the previous sub-model's uncertainty is the trade flows in tonnages ($t_{i,j,k,l,m,n}$). All inputs are multidimensional, meaning that there are several values for each one, even for the same dataset. For example, there are millions of supply chains ($i,j,k,l,m,n$) and therefore there are millions of supplies chain shares and value-weight ratios. Thus, even though the model is simple, the multidimensional variables coupled with added source data variation for each input increases the computation effort needed for repeated simulation.

Identifying the affected outputs is also straightforward for this model as each equation is a linear equation with one output. The output of the first sub-model, the disaggregated trade flows in monetary value ($z_{i,j,k,l,m,n}$), is directly affected by any uncertainty in the supply chain share inputs ($s_{i,j,k,l,m,n}$). The output of the second sub-model, the disaggregated trade flows in weight ($t_{i,j,k,l,m,n}$), is affected by the uncertainty in the value-weight ratios ($w_{i,j,k,l,m,n}$) and the disaggregated trade flows in monetary value ($z_{i,j,k,l,m,n}$). The output of the third sub-model, the aggregated domestic trade flows ($t_{j,k,d}$), is affected by the uncertainty in the domestic mode shares ($s_{i,j,k,d}$) and the disaggregated trade flows in weights ($t_{i,j,k,l,m,n}$). Notice that due to the successive nature of the sub-models, the uncertainty introduced at each step most likely affects the outputs of each successive step. Moreover, these outputs are also multidimensional.

The datasets available for each source of uncertainty were already introduced in Section 3.2. Table 10 is a summary of this information organized for each sub-model of the freight model and their respective inputs.

**Table 10 Summary of Data Available on Sources of Uncertainty**

| Sub-Model | Inputs | Data Available |
|---|---|---|
| Trade Flow Disaggregation | GTAP forecasts | Forecasts for 2015, 2035, and 2035 after CPTPP. |
| | Supply chain shares | CBSA export data for 2010-2015 (6 years) |
| Value to Quantity Transformation | Disaggregated trade flows ($) | Output of previous sub-model |
| | Value-weight ratios | Value and weight data for 2008 at the 5-digit SCTG level |
| Domestic Mode Splits | Disaggregated trade flows (tonnes) | Output of previous sub-model |
| | Domestic mode shares | CFAF domestic freight data for 2011-2017 (7 years) |

### 3.3.2. Step 2: Input Uncertainty Distributions

The goal of this step is to identify the form of variation that is going to be used in the repeated simulation step. One route is to estimate or assign probability distributions to the inputs identified in the previous step. Another is to use historical data, if available, to vary the input base year using exclusively empirical data.

Estimating the probability distribution of the inputs is difficult. Estimating the central value and dispersion of the inputs may be done using available data, for example, using time series data (Manzo, 2014). The difficulty arises in defining the distribution type (Manzo, 2014). In the literature, multiple studies have used univariate or multivariate normal and log-normal distributions to estimate the variation of the inputs in transportation demand models (de Jong et al., 2007; Manzo, 2014; Rasouli & Timmermans, 2012; Zhao & Kockelman, 2002). For example, De Jong et al. (2007) used 20 year historical data to calculate moving means and standard deviations for their inputs before assuming a multivariate normal distribution. Similarly, Zhao and Kockelman (2002) used point estimates (means) from the Dallas-Ft. Worth travel model's dataset and assumed both the coefficients of variation (0.30) and lognormal distributions for their inputs and model parameters.

On the other hand, using historical data to directly vary different values for the desired input is easier and requires fewer assumptions. Often a base year for a certain input variable is used when developing models. This strictly empirical method works in situations where multiple years of data are available, and the model is simple enough to run for all possible combinations while changing the base years of the inputs. The major assumption required to use this method is that the temporal variation exhibited in the years of data available continues, sincethe researcher is taking values directly from each year as opposed to estimating distributions using time series analysis. This assumption is generally valid in the practice of transportation demand modelling as modellers are often forced to arbitrarily choose base years (based on available data) to develop models and do not engage in a full time series analysis due to lack of resources. Thus, this method incorporates this general assumption used in practical modelling along with the assumption that more data (or resources) are not available to fully conduct a time series analysis.

It is not necessary to examine the parameters and types of the distributions of the identified sources of uncertainty for the case study. The identified sources of uncertainty are empirically calculated using the available datasets. Thus, variation can be created by simply calculating those inputs using all available datasets and incorporating the assumption, discussed above, that the temporal variation presented in those datasets continues. Then, repeated simulation can be ran using all calculated inputs. More details of this procedure are provided in the explanation of the repeated simulation step that follows.

The variation for the identified input of the first and third sub-models are simple. The supply chain shares are varied over all available CBSA data years 2010-2015 (six years/runs). Similarly, the domestic mode shares are varied over all available CFAF data years 2011-2017 (seven years/runs).

The variation for the value-weight ratios is more catered towards this case study's analyses. Sector classification systems provide different levels of detail with their codes. For example, the SCTG five-digit code 02200 is for commodities that are "corn except sweet, but including seed and corn for popping", whereas the two-digit equivalent code 02 is for commodities that are "cereal grains" (Statistics Canada, 2015). Usually, detail increases with an increasing number of digits. It can be argued that sectoral detail is important in this type of analysis since FTAs often have highly detailed commodity-specific policies. This can be explored by varying the sectoral detail. Thus, the value-weight ratios are varied by changing the number of digits on the SCTG codes (i.e., aggregating over digits to lower resolution). Five-digit (base case), four-digit, three-digit, and two-digit aggregations are explored in the repeated simulations (4 aggregations/runs).

### 3.3.3. Step 3: Simulation

After the form of variation for the desired inputs is identified, the next step is to use repeated simulation. Essentially, the model is run as many times as possible. Stochastic simulation is preferred in the case where distributions were estimated to avoid further bias introduced by the modeller. Repeated simulation using random draws is referred to as Monte Carlo simulation. The problem with stochastic simulation is the large amount of runs necessary for unbiased results. There are other forms of semi-random or quasi-random draws that can be used in order to lower the number of runs needed while still obtaining less biased results. Table 11 is a summary of the sampling techniques identified in the literature.

**Table 11 Sampling Techniques for Repeated Simulation**

| Technique | Description | e.g. |
|---|---|---|
| Monte Carlo | Random draws are taken from input/parameter distributions to use in repeated simulations | (Zhao & Kockelman, 2002) |
| LHS | Stratified random draws are taken from input/parameter distributions to use in repeated simulations.<br>The cumulative distribution of variables is divided into equal intervals and one random value is taken from each interval. | (Yang & Chen, 2009) |
| Factorized Design | Stratified random draws are taken from input/parameter distributions to use in repeated simulations.<br>The cumulative distribution of variables is divided into equal intervals and the mid-percentile value is taken from each interval. | (Pradhan & Kockelman, 2002) |
| Halton Draws | Quasi-random draws are taken from input/parameter distributions to use in repeated simulations.<br>The quasi-random draws are based on a form of the Halton Sequence. (Daly et al., 2003) | (de Jong et al., 2007) |
| Sobol Method | Quasi-random draws are taken from input/parameter distributions to use in repeated simulations.<br>The quasi-random draws are based on a form of the Sobol method explained in Saltelli (2002). | (Bao et al., 2016) |

Repeated simulation using all available combinations is preferred in the case where historical data are being used directly. If it is possible, all years available for each input should be used. For example, if ten years of data for input A and 5 years of data for input B are available, then the simulation should be repeated 50 times or 50 runs of the model. This ensures that all available empirical information is being utilized and less bias is introduced by unnecessary assumptions.

The results are then extracted exclusively from the empirical data without assumptions about the types or parameters of the distributions.

For the case study, the repeated simulations have a total of 168 runs. Table 12 summarizes the variation introduced at each sub-model. After this, a mathematical representation of the repeated simulation is presented and explained.

**Table 12 Summary of Variation Used in Simulation**

| Sub-Model | Inputs | Variation |
|---|---|---|
| Trade Flow Disaggregation | GTAP forecasts | Constant (out of scope) |
| | Supply chain shares | 6 years (2010-2015) |
| Value to Quantity Transformation | Disaggregated trade flows ($) | 6 sets (output of previous model) |
| | Value-weight ratios | 4 digit aggregations |
| Domestic Mode Splits | Disaggregated trade flows (tonnes) | 24 sets (output of previous model) |
| | Domestic mode shares | 7 years (2011-2017) |
| Final Result/Output | Domestic O-D flows | 6 years x 4 digit aggregations x 7 years = 168 versions |

Adding the variation to the supply chain shares, the first sub-model becomes:

$$z_{y,i,j,k,l,m,n} = s_{y,i,j,k,l,m,n} \times z_{i,l} \tag{4}$$

where $z_{y,i,j,k,l,m,n}$ is the trade flow ($) (disaggregated) for CBSA year *y* of commodity *i* produced in subnational region *j* exported by subnational region *k* to country *l* by international mode *m* through port of clearance *n*. $s_{y,i,j,k,l,m,n}$ is the international export share for CBSA year *y* of commodity *i* produced in subnational region *j* exported by subnational region *k* to country *l* by international mode *m* through port of clearance *n*, determined from initial shares in the export trade data. $z_{i,l}$ is the international trade flow ($) of commodity *i* to country *l*, from the CGE model results (Dade et al., 2017).

For the first sub-model there are six possible years that can be used to calculate supply chain shares. Using the available CBSA export data, six different supply chain shares ($s_{y,i,j,k,l,m,n}$) are calculated. The *y* subscript denotes the CBSA export data year used to calculate that share. The shares are then fed into the first sub-model which in turn creates six sets of disaggregated trade flows in monetary values ($z_{y,i,j,k,l,m,n}$).

Similarly, with the added variation to the previous model and the value-weight ratios with varied aggregation levels, the second sub-model becomes:

$$t_{y,a,i,j,k,l,m,n} = \frac{z_{y,i,j,k,l,m,n}}{w_{a,i,j,k,l,m,n}} \tag{5}$$

where $t_{y,a,i,j,k,l,m,n}$ is the trade flow (tonnes) for CBSA year *y*, with SCTG digit aggregation *a*, of commodity *i* produced in subnational region *j* exported by subnational region *k* to country *l* by international mode *m* through port of clearance *n*. $w_{a,i,j,k,l,m,n}$ is the value-weight ratio ($/tonnes) with SCTG digit aggregation *a*, for shipments of commodity *i* produced in subnational region *j* exported by subnational region *k* to country *l* by international mode *m* through port of clearance *n*.

There are four different SCTG digit aggregations to use in the calculation of the value-weight ratios ($w_{a,i,j,k,l,m,n}$). The subscripts *a* represents each aggregation: 5-digit, 4-digit, 3-digit, and 2-digit meaning that there are four different sets of value-weight ratios. Adding the variation of the previous step, the output of this step ($t_{y,a,i,j,k,l,m,n}$) has 6x4 (*y* x *a*) sets of values.

Finally, the third sub-model becomes the following after the uncertainty of domestic mode shares is added:

$$t_{y,a,b,j,k,d} = \sum_i \left( s_{b,i,j,k,d} \times \sum_l \sum_m \sum_n t_{y,a,i,j,k,l,m,n} \right) \tag{6}$$

where $t_{y,a,b,j,k,d}$ is the total trade flows (tonnes) for CBSA year *y*, with SCTG digit aggregation *a*, for CFAF year *b*, shipped from subnational region *j* to subnational region *k* by domestic mode *d*. $s_{b,i,j,k,d}$ is the share for CFAF year *b*, of commodity *i* shipped from subnational region *j* to subnational region *k* by domestic mode *d*.

There are seven set of domestic mode shares ($s_{b,i,j,k,d}$) because the CFAF database provided seven years of data 2011-2017. The subscript *b* represents each CFAF year. Adding the variation of the previous two models, the final output of the freight model has 6 x 4 x 7 = 168 (*y* x *a* x *b*) sets of values.

The 168 simulations outline above were performed for all three CGE economic forecast inputs: 2015, 2035, 2035 with CPTPP. The results obtained using the latter forecast, 2035 trade flows after CPTPP policy shocks, is often referred to as CPTPP on result figures for the sake of brevity.

### 3.3.4. Step 4: Estimation of Output Distribution and/or Distribution Parameters

Using the data generated in the repeated simulation, distributions for the outputs can be estimated. This step is similar to estimating the distribution of the inputs. However, the data that are used to calculate the point estimate (mean) and dispersion (standard variation) is the set of values generated for each output during the repeated simulation step. This can be done for each sub-model output or outputs, if the model consists of successive sub-models (e.g., a traditional four-step model). If the number of runs is large enough, the distribution type can be assessed using a histogram analysis for a more informed assumption than simply assuming normal or lognormal distributions. Assessing the distribution type may be difficult if the number of outputs is large.

It is desirable to assume that the outputs are normally distributed since this is the most utilized and understood probability distribution. Unlike nonparametric tests, there are multiple parametric statistical tests that require some form of normality to be assumed. For example, regression analysis and subsequent analysis of variance (ANOVA) require the residuals to be normally distributed. A more formal normality test such as a normal probability plot (NPP) can be used to assess if a dataset can be safely assumed to be normally distributed. If the data are not readily normally distributed, then a transformation may be used so that the transformed data are normally distributed. However, the normality assumption for a lot of parametric tests regards the sample mean. Thus, if the observations themselves are not normal, some parametric statistical tests can still be used.

This step of the framework is very difficult for this case study. The multidimensional outputs contain millions of individual sets of simulated observations. For example, after the second sub-model, there are over 190 million sets of trade flows (tonnes) with 24 observations each. The distributions need to be assessed for each of those sets using the 24 observations generated through the simulation step. Statistical analysis of the outputs is performed using some assumptions and the aid of the central limit theorem due to the very difficult task of estimating the distribution of millions of outputs. More details on these procedures and assumptions are provided in the following section.

### 3.3.5. Step 5: Analysis of Results and Discussion

The analysis portion of this framework relies heavily on statistical analyses as the results are obtained through repeated simulation. Depending on the outcome of the previous step, further analysis of the distribution type may be required. For example, if the distribution of the outputs cannot be easily estimated, or if they are not normally distributed, the central limit theorem can be used to justify the usage of some powerful parametric statistical tests (i.e., confidence intervals, t-tests, ANOVA, etc.).

#### 3.3.5.1. Importance of the Normal Distribution

The normal distribution is a highly desirable assumption as it is well understood and has desirable properties. The normal distribution is presented in the equation below.

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} exp\left\{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right\} \quad (7)$$

where $\mu$ is the mean, and $\sigma^2$ is the variance. These two parameters describe its shape. The shape of a typical normal distribution is a bell curve as depicted in Figure 14. However, this figure depicts the standard normal distribution with a mean of 0 and variance of 1.

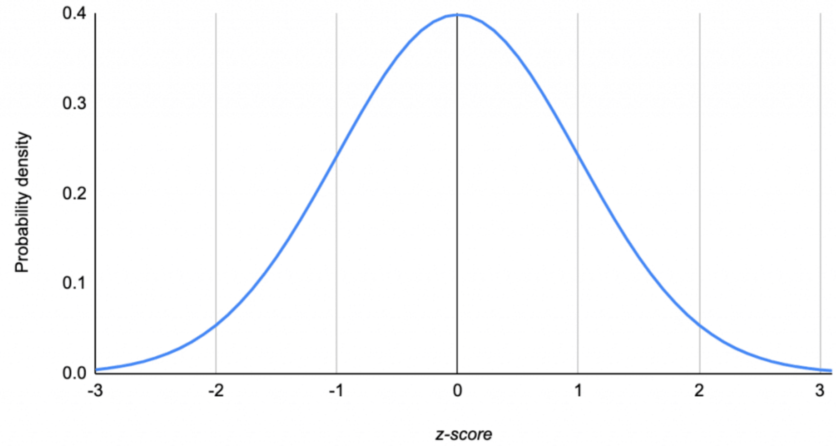


**Figure 14 Standard Normal Distribution (Bhandari, 2020)**

The standard normal distribution along with *z*-score tables (denoting the area under the curve between *0* and *z* standard deviations above the mean) are used to run hypothesis testing on the population mean ($\mu$) and the population variance ($\sigma^2$). This is a type of parametric statistical test, but it is almost never used because it assumes that true population parameters ($\mu$ and $\sigma^2$) are known. This is generally not the case as researchers often work with a sample of the population with a given sample size ($N$), sample mean ($\bar{X}$), and sample variance ($S^2$).

One of the main advantages of using the normal distribution is its symmetry. As a result of symmetry, the mean, median, and mode are all the same. Additionally, exactly half of the population or sample is greater than the mean and half is smaller than the mean. This allows researchers to determine the exact proportions of values that fall within a distance, often measured in standard deviations ($S$), from the mean. This is also known as the Empirical Rule that states 68% of normally distributed observations fall within one standard deviation, 95% within two standard deviations, and 99.7% within three standard deviations (The Pennsylvania State University, 2021).

Another advantage of the normal distribution is that if a population is normally distributed then its sample mean and sample variance are independent of each other provided that it is a random sample of the population (Mordkoff, 2016). This means that any error in the estimation of the sample mean is independent of any error in estimating the sample variance. This property only occurs in the normal distribution, and it simplifies the mathematics of further analyses (Mordkoff, 2016).

#### 3.3.5.2. Testing the Normality Assumption

There are two well-established ways to test for normality: plotting methods and nonparametric statistical tests. Plotting methods include histograms, normal probability plot, stem-and-leaf plots, boxplots, probability-probability plots, and quantile-quantile plots. Common normality tests include the Kolmogorov-Smirnov (K-S) test, Lilliefors corrected K-S test, Shapiro-Wilk (SW) test, D'Angostino-Pearson (DAP) omnibus test, and the Jarque-Bera (JB) test (Öztuna et al., 2006).

Normal probability plots are a tool used to determine if a sample comes from a normal distribution. A detailed procedure to construct an NPP can be found in Montgomery (2005). Software packages often have NPPs included in them as well. Figure 15 is an example of an NPP. A sample is considered normal if the observations follow a straight line on an NPP. It is recommended to place more emphasis on the central values of the plot rather than the extremes when visualizing a line (Montgomery, 2013). An advantage of a graphical method, such as constructing NPPs, is that the researchers can detect outliers and judge the normality of the bulk of the data, thus making conclusions more robust.

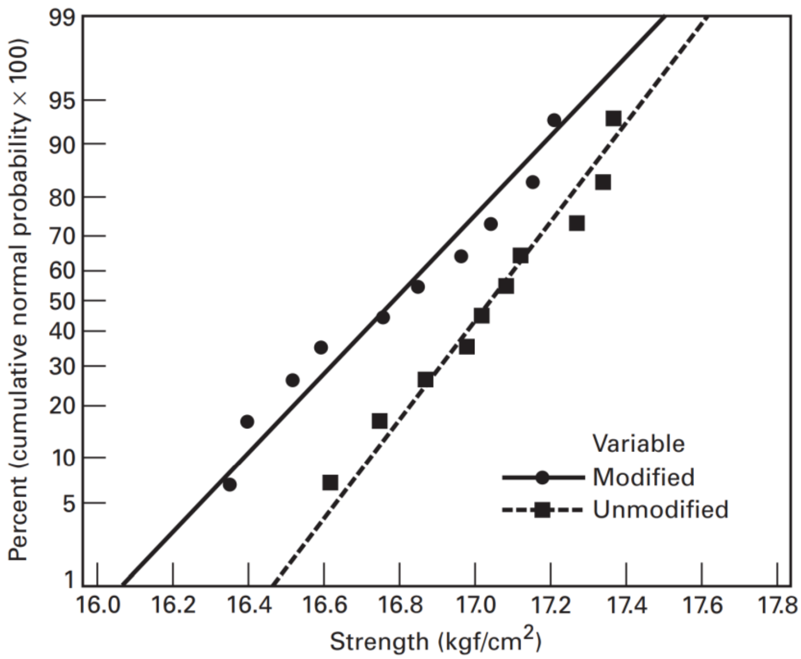


**Figure 15 Example of a Normal Probability Plot (Montgomery, 2013)**

In the testing methods, the null hypothesis ($H_0$) is that "the sample distribution is normal". Therefore, if the p-value is higher than the significance level ($\alpha$) then there is insufficient statistical evidence to reject $H_0$ and the sample is normally distributed. A test's power is the probability of not committing a Type I Error (i.e., incorrectly rejecting the $H_0$). A study found that the JB test was the most powerful meaning that it was the least likely to commit Type I Error, and the SW test was the best to correctly identify that a distribution was non-normal (Öztuna et al., 2006). However, that study did not include outlier points which are often found in real data; they tested variables that were forced to a particular distribution. Thus, their findings do not include how sensitive a test is to outliers.

In normality testing, robustness is how sensitive a test is to outliers or small deviations from normality. This is common drawback of most available normality tests (Stehlík et al., 2014). Stehlik et al. (2014) concluded in their study that an unambiguous conclusion cannot be drawn in terms of the best or most robust test and further explained that this is an inherent problem when comparing normality tests. Essentially, there is not a test that is inherently the most powerful test for normality (Stehlík et al., 2014). For this reason, it is recommended to use graphical methods, when possible, although this requires a researcher that has adequate knowledge to correctly assess the plots.

Out of the tests, the most widely applied ones are the K-S and SW nonparametric tests (Mishra et al., 2019; Mordkoff, 2016). The K-S test is known to be highly sensitive to outliers and it is not recommended for occasions when parameters are estimated from data (e.g., simple linear regression) (Steinskog et al., 2007). A study found that even after the modifications by Lilliefors (1967) and later by Dallal and Wilkinson (1986), the JB and SW tests have more power than the modified K-S test. Typically, the K-S test is used for larger sample sizes (>50) and the SW test is used for smaller sample sizes (<50) (Mishra et al., 2019). The SW test is recommended in various studies as it resulted in the best power under different circumstances detailed in their studies (Farrell & Rogers-Stewart, 2006; Keskin, 2006; Mendes & Pala, 2003; Mohd Razali & Bee Wah, 2011; Öztuna et al., 2006; Romão et al., 2010; Yap & Sim, 2011; Yazici & Yolacan, 2007). However, a review of these studies concluded that for small sample sizes (<50), the power of the SW tests were small and always under 0.5 (Ruxton et al., 2015). This means that there is a less than 50% probability that the SW test will not commit Type I Error (i.e., incorrectly reject the $H_0$). In terms of normality testing, there is less than a 50% probability that the test correctly found enough statistical evidence to prove that the sample is not normally distributed.

The Shapiro-Wilk test is widely available in software packages. The null hypothesis ($H_0$: sample is normally distributed) is rejected if the calculated W statistic is below a critical value. The W statistic can be calculated through the following equation:

$$W = \frac{\left(\sum_{i=1}^{nN} a_i x_i\right)^2}{\sum_{i=1}^{nN}(x_i - \bar{x})^2} \tag{8}$$

where: $x_1,\ldots,x_N$ are sample values ordered from smallest to largest, $a_1,\ldots,a_N$ are weights (most software packages use the algorithm by Royston (1995)) (Ruxton et al., 2015), and $N$ is sample size.

The denominator has the same form as the equation for the variance of a sample ($S^2$), and the numerator is related to the best estimation of the sample variance if it were drawn from a normal distribution (Ruxton et al., 2015). As mentioned above, the power of this test decreases with sample size (Ruxton et al., 2015).

#### 3.3.5.3. The Central Limit Theorem

The Central Limit Theorem (CLT) is often used to justify the assumption of normality behind parametric statistical tests. The CLT states that for a random variable ($X$) with population mean ($\mu$) and population variance ($\sigma^2$), the distribution of sample means ($\bar{X}$) of sample size $N$ approaches normality as $N$ increases regardless of the distribution of $X$ (Montgomery, 2013) . There are many cases where the CLT applies even at very small sample sizes (N<10) (Montgomery, 2005). However, the more skewed the distribution of $X$, the larger the sample size has to be for the CLT to apply (Montgomery, 2013). In the literature, sample sizes of 20-30 are often used as the lower limit to apply CLT. These numbers are in part based on empirical analyses using the exponential distribution because its shape is very different from the shape of the normal distribution (Mordkoff, 2016).

#### 3.3.5.4. Parametric and Nonparametric Tests

Parametric tests require some form of normality assumption whereas nonparametric tests do not require this. In most cases, parametric tests can be used as they are relatively insensitive to small deviations from normality and the CLT can be applied under certain circumstances (Montgomery, 2013). For example, constructing confidence intervals using the t-test statistic value requires the sample means ($\bar{X}$) to be normally distributed which can be justified using the CLT regardless of the distribution of the original sample (Penlindis, 2019). Non-parametric tests have the advantage of not needing any normality assumption. Additionally, data can be categorical or rank data (Montgomery & Runger, 2010). However, parametric tests tend to be more powerful than nonparametric tests for the same sample size (Chin & Lee, 2008). The following table is a summary of available parametric tests for means and their nonparametric counterparts for medians.

**Table 13 Parametric and Nonparametric Tests for Similar Analyses (Frost, 2021)**

| Parametric Tests of Means | Nonparametric Tests of Medians | Null Hypotheses |
|---|---|---|
| 1-sample t-test | 1-sample Sign test, 1-sample Wilcoxon | $H_0$: mean/median ≥ or ≤ or = hypothesized value |
| 2-sample t-test | Mann-Whitney test | $H_0$: mean/median of sample 1 = mean/median of sample 2 |
| One-Way ANOVA | Kruskal-Wallis[2] median test, Mood's median test | $H_0$: mean/median of sample 1 = …. = mean/median of sample $k$[3] |
| Factorial DOE[1] with a factor and a blocking variable | Friedman test | Like One-Way ANOVA but with blocking variables |

[1]Design of Experiments
[2]Kruskal-Wallis test can also test the mean ranks
[3]$k$ is the number of samples

#### 3.3.5.5. Transformations

As explained previously, the normal distribution is highly desirable for different statistical analysis. Thus, if the output is found not to be normally distributed and this is necessary for the type of analysis (e.g., simple regression for simplicity and transparency (Penlindis, 2019)), a transformation may be tried. Common transformations of independent variables ($X$) (i.e., outputs or responses) are $log(X)$, $1/X$ and $\sqrt{X}$ (Penlindis, 2019). One popular method to determine an appropriate transformation is the Box-Cox method. A detailed explanation of this method is provided in Sakia (1992).

### 3.3.5.6. Application of Step 5 to Case Study

There are three different types of results discussed in the case study. First, the outputs of each sub-model are referred to as disaggregated outputs. Second, in a preliminary analysis of the CPTPP effects using this model, the results were presented in aggregated tables to allow for major conclusions to be drawn (e.g., for major gateways, corridors, and ports). These are referred to as aggregated outputs. Lastly, two specific sets of *i, j, k, l, m, n, d* combinations are selected for a targeted analysis. One set covers the usage of the freight model as a trade growth analysis tool only and the second set covers the usage of the model as an FTA analysis tool. To that end, the first set is centered around the US, a major non-CPTPP Canadian trade partner, and the second set is centered around the CPTPP signatories. These are subsequently referred to as the targeted outputs.

The analysis for this study is threefold. First, the disaggregated outputs of each sub-model are analyzed by calculating descriptive statistics, creating confidence intervals about the population means, and comparing these intervals to the base case values. Second, the outputs are aggregated to recreate the results of the preliminary base case study. These results consist of aggregations of export results for major Canadian gateways, aggregations of results by ports of entry to establish the top ten ports, and the presentation of domestic movement summary tables. Descriptive statistics and confidence intervals are calculated for these aggregated scenarios, and they are compared to the base case to assess similarities and differences. The aggregated results by ports are also analyzed using rank error measurements (Xaykongsa, 2021) since they are a ranked list (i.e., most impacted to least). Lastly, two targeted analyses are presented to illustrate the correct procedure of results analysis including formal normality assumption checks, confidence intervals creation, and comparison to the base case. The targeted analyses are meant to not only illustrate a correct procedure for the analysis of these types of results, but also assess the uncertainty associated with the modelling of regular trade growth versus modelling the uncertainty of FTA policy shocks on trade over 20 years. The normality checks used are the SW test and NPPs (described in Section 3.3.5.2). More details on the different statistical analyses and assumptions are provided in Chapter 4.

# Chapter 4. Results and Discussion

The simulations were performed as described in Section 3.3.3 using Python version 2.7. Disaggregated outputs for each sub-model ($z_{y,i,j,k,l,m,n}$, $t_{y,a,i,j,k,l,m,n}$, $t_{y,a,b,j,k,d}$) were obtained. Then, following the preliminary analysis performed for the base case, aggregated output tables were created. Finally, a detailed analysis was performed on two targeted results.

The following sections present the outputs, the statistical analyses performed on the results, and a discussion of findings for the three types of results obtained (disaggregate, aggregate, and targeted).

An important aspect of the results are the monetary values and their reference years. All monetary values were transformed to 2015 CAD, which is the unit of the base case. This is done to properly calculate the descriptive statistics and perform other comparative analyses. Otherwise, the results would be misleading because they would technically be in different units from year to year (i.e., a 2011 CAD is not worth the same as a 2015 CAD).

## 4.1. Disaggregated Outputs

This section is divided into two: analysis of the data using descriptive statistics, and analysis of the data using confidence intervals.

Descriptive Statistics Analysis

After the simulations were performed, three outputs were collected directly from each sub-model. Descriptive statistics were then calculated for each set of observations. For example, for the disaggregated trade flow values ($z_{y,i,j,k,l,m,n}$), the output of the first model, over 190 million sample means, sample standard deviations and sample coefficient of variations were calculated using the 6 observations for each supply chain ($i,j,k,l,m,n$). Notice that since a source of uncertainty was varied at each step, the outputs of each step vary over a different set of runs or observations. For example, the disaggregated trade values ($z_{y,i,j,k,l,m,n}$) only vary over 6 runs of the simulation as they are only affected by uncertainty on the supply chain shares ($s_{y,i,j,k,l,m,n}$). Table 14 summarizes the outputs for each sub-model.

**Table 14 Dimensionality of Descriptive Statistics for Disaggregated Outputs**

| Sub-Model | Output | No. of Observations | Descriptive Statistics |
|---|---|---|---|
| Trade Flow Disaggregation | Disaggregated Trade Flows (CAD) $z_{y,i,j,k,l,m,n}$ | 6 | $\bar{X}_{i,j,k,l,m,n}$, $S_{i,j,k,l,m,n}$, $COV_{i,j,k,l,m,n}$ |
| Value to Quantity Transformation | Disaggregated trade flows (tonnes) $t_{y,a,i,j,k,l,m,n}$ | 24 | $\bar{X}_{i,j,k,l,m,n}$, $S_{i,j,k,l,m,n}$, $COV_{i,j,k,l,m,n}$ |
| Domestic Mode Splits | Domestic Trade Flows $t_{y,a,b,i,j,k,d}$ | 168 | $\bar{X}_{i,j,k,d}$, $S_{i,j,k,d}$, $COV_{i,j,k,d}$ |

To further illustrate the calculation of the descriptive statistics, the outputs of the first sub-model are used as an example below:

$$sample\ mean = \bar{X}_{i,j,k,l,m,n} = \frac{1}{N}\sum_{y=1}^{N} Z_{y,i,j,k,l,m,n} \tag{9}$$

$$sample\ variance = S^2{}_{i,j,k,l,m,n} = \frac{\sum_{y=1}^{N}\left(z_{y,i,j,k,l,m,n}-\bar{X}_{i,j,k,l,m,n}\right)^2}{n-1} \tag{10}$$

$$sample\ standard\ deviation = S_{i,j,k,l,m,n} = \sqrt{S^2{}_{i,j,k,l,m,n}} \tag{11}$$

$$sample\ coefficient\ of\ variation = COV_{i,j,k,l,m,n} = \frac{S_{i,j,k,l,m,n}}{\bar{X}_{i,j,k,l,m,n}} \tag{12}$$

where $N$ is the total number of observations. In the example above, $N$ is 6.

The resulting descriptive statistics are multidimensional. Each set of subscripts refers to a different supply chain (sub-models 1 and 2) or domestic movement (sub-model 3). For this reason, the sample means and sample variances are highly different from each other. Moreover, the units of these values are not constant. In the first sub-model, the units of the sample means and sample standard deviations are in 2015 CAD, whereas the second and third sub-models have units of weight (tonnage). This makes these values incomparable between sub-models.

To facilitate comparisons, sample COVs are calculated. These are unitless ratios of noise (sample standard deviation) to signal (sample mean), meaning they measure the dispersion of the data. Typically, a COV that is less than one is considered "low variance" meaning that the noise is smaller than the signal. Conversely, a COV larger than one is considered "high variance" meaning that the noise is larger than the signal. In normally distributed variables, higher variances mean that the bell curve is wider. Due to the unitless property of COVs, comparisons between sets with very different means is feasible. These are the measures used to compare the uncertainty at each step of the freight demand model.

As shown on Figure 15, the COVs were pooled and averaged for each sub-model and the 5th and 95th percentiles were calculated for all three economic model forecasts 2015, 2035 and 2035 after CPTPP. This analysis is similar to the one conducted by Zhao and Kockelman (2002). On the *x*-axis trade values refer to the outputs of the first sub-model ($z_{i,j,k,l,m,n}$), trade quantities refer to the outputs of the second sub-model ($t_{i,j,k,l,m,n}$), and domestic quantities refer to the outputs of the third sub-model ($t_{j,k,d}$). Appendix A – 2035 Forecast Mean COVs for the Outputs of Each Sub-model examples of more disaggregated mean COVs using the 2035 CGE forecast.

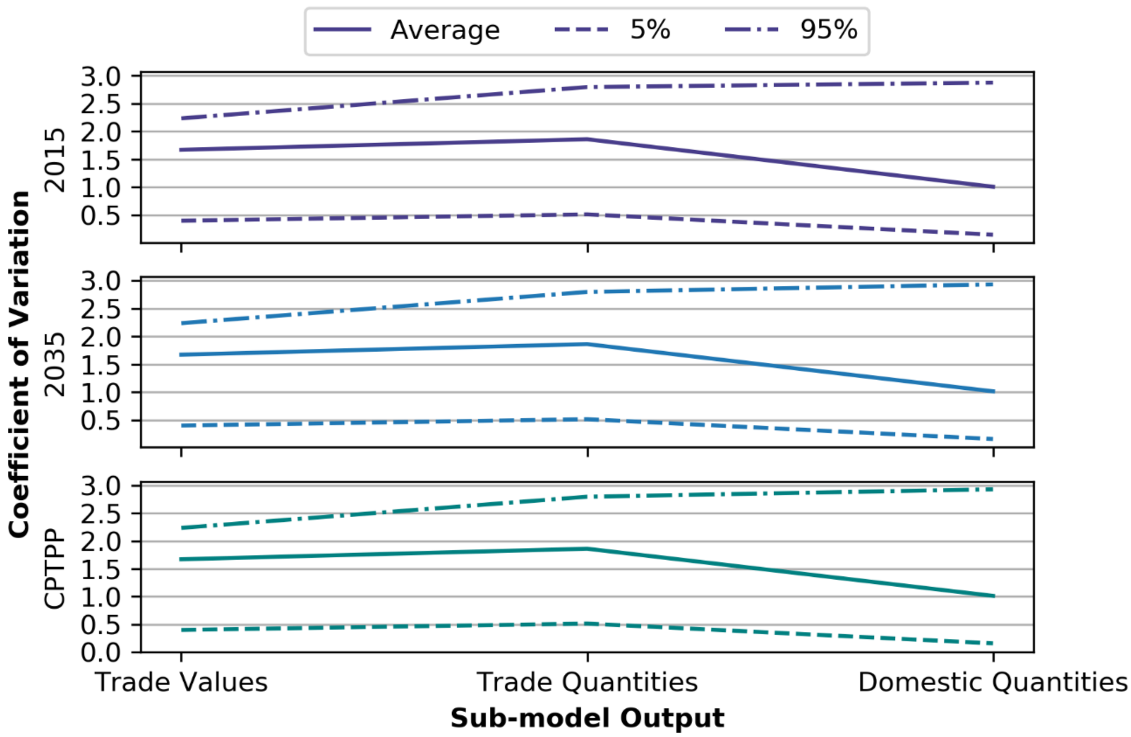


**Figure 16 Mean COVs for Each Sub-model (All Forecast Years)**

There are no obvious differences between the results for the outputs of sub-models for the three CGE forecasts. This is expected due the nature of the GTAP CGE model. CGE models are specified to reproduce an initial economy (base year). The base year economy in the dynamic GTAP model is the GSC2 sector market of 2011 with its 40 regions. This is an exact calibration rather than a statistical one, meaning that forecasted year equilibria are solved using the same parameters and assumptions as for the base year. There are differences in the results for combinations of sectors and regions. However, the number of values for a given forecasted year is large and the set of rules to solve the equilibria is constant. Consequently, there is not enough deviation to notice on the COV means between forecast years when the descriptive statistics are calculated on the results of the freight model and they are further averaged. Thus, one economic forecast can be examined alone, as on Figure 17.

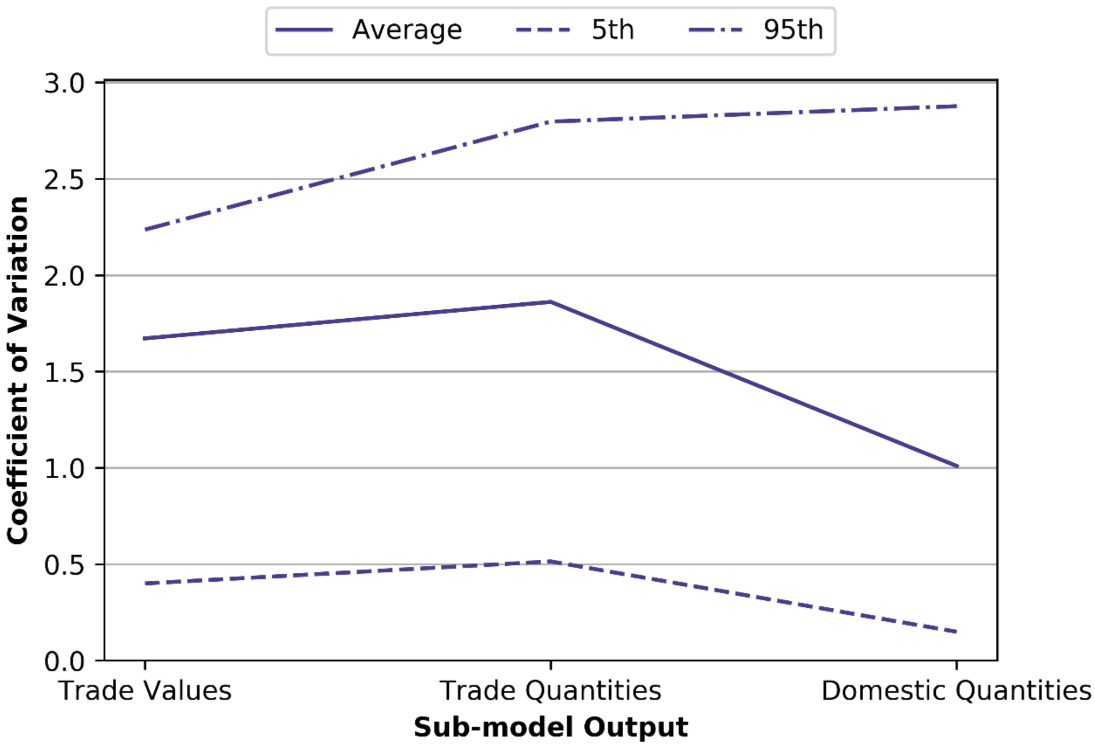


**Figure 17 Mean COVs for Each Sub-model (2015 CGE Forecast)**

The means of the COVs over each sub-model are all higher than one. This means that on average, all the sub-models exhibit high variance of their outputs. The trend of the mean COVs shows that there is an increase in the dispersion of the outputs of the first sub-model and the second sub-model, and then a sharper decrease between the second and third sub-model. By the last sub-model, the mean dispersion of the domestic trade flows ($t_{j,k,d}$) is close to one and lower than the mean dispersion of the outputs of the first sub-model ($z_{i,j,k,l,m,n}$).

In the space between the 5th percentile and 95th percentiles lie 90% of the COVs. These additional lines allow conclusions to be made about the majority of the COVs. For the outputs of the first sub-model ($z_{i,j,k,l,m,n}$), 90% of the COVs are contained within the values ~0.4 to ~2.2. If a distribution of the COVs for this sub-model was estimated it would be skewed towards high variance values (i.e., above one), meaning that more observations are above one than below one since the mean line is closer to the 95th percentile line. Over 50% of those COVs are higher than the mean of ~1.7. This is because medians or 50$^{th}$ percentiles tend to be further towards the extremes than the means on skewed distributions (see Figure 18). For the outputs of the second sub-model ($t_{i,j,k,l,m,n}$), 90% of the COVs are contained within the values ~0.5 to ~2.8. This range is larger than the previous step, meaning that not only did the mean dispersion increase, but the variation of the dispersion (COVs) also increased from the first sub-model to the second. For these outputs ($t_{i,j,k,l,m,n}$), more than 50% of the COVs are higher than the mean of ~1.9. The trend of increasing dispersion of the COVs continued further on the third sub-model, where 90% of the COVs of its outputs ($t_{j,k,d}$) are between ~0.1 and ~2.9. However, at this sub-model, the distribution of the COVs is skewed towards the lower values. This means that over 50% of the COVs have values below their mean of ~1.0. Unlike the other two sub-models, the majority of outputs ($t_{j,k,d}$) for this sub-model have low variance.

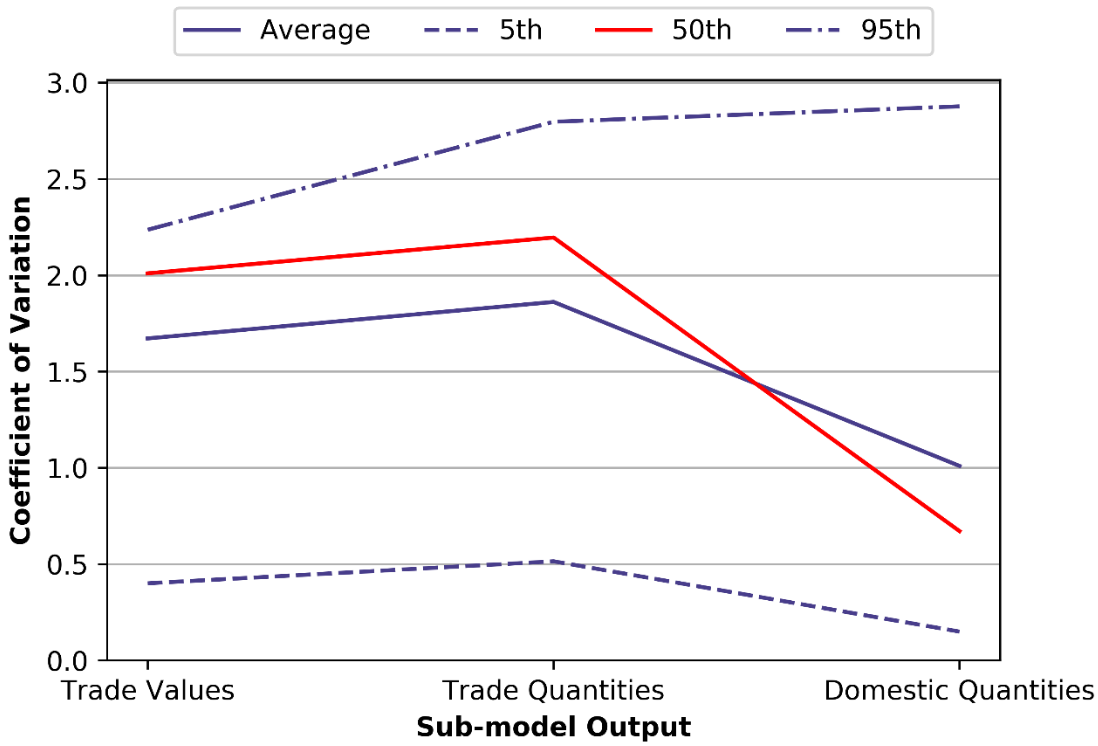


**Figure 18 Mean COVs for Each Sub-model with Medians (2015 CGE Forecast)**

The trends exhibited by the mean COVs are reasonable. The first two sub-models have outputs that are highly disaggregated with over 190 million unique supply chains. It is reasonable that the measure of dispersion on average increased from the first model output ($z_{i,j,k,l,m,n}$) to the next ($t_{i,j,k,l,m,n}$) since an additional source of uncertainty, the SCTG code aggregation scheme used to calculate the value-weight ratios ($w_{i,j,k,l,m,n}$), was introduced. The last sub-model output ($t_{j,k,d}$) is more aggregated than the first two by six orders of magnitude, with 363 distinct domestic movement combinations. For this reason, the mean dispersion of this output ($t_{j,k,d}$) is lower than even the first sub-model's output despite a new source of uncertainty introduced as well (variation on the domestic shares due to seven years of CFAF data). Thus, the trends seen in the mean COVs are within reason.

The calculation of the percentiles revealed more interesting observations. An interesting finding is that the range of the observed COVs increased over all sub-models. Thus, by the last sub-model there are values of dispersion as high as ~2.8. Calculating the percentiles also showed an interesting finding regarding dispersion of the outputs at each sub-model. For the first two sub-models, the percentile analysis shows the same results as the mean COVs since the distribution of the dispersion values are skewed towards values that indicate high variance of those outputs. However, for the third sub-model, the percentile analysis differs from the mean COV conclusion and shows that in fact most of the COVs (over 50%) have values that indicate low variance of the outputs ($t_{j,k,d}$) - meaning that over 50% of the domestic movement combinations ($j,k,d$) exhibit low variance. Ultimately, the high aggregation that occurs between the second sub-model and the third is enough to lower the dispersion for the majority of domestic movements to low variance.

Confidence Interval Analysis

Confidence intervals (CI) can be constructed around a population parameter. CIs are ranges where the true value of a parameter is expected to lie. The general formulation for a confidence interval of a parameter $\theta$ is presented below:

$$CI\colon\ \bar{\theta}\ \pm (multiplier)\sqrt{Var(\theta)} \tag{13}$$

where $\bar{\theta}$ is the parameter estimate and $Var(\theta)$ is the variation of the chosen parameter. The multiplier depends on the distribution of the parameter ($\theta$), the confidence level ($1\text{-}\alpha$) or significance ($\alpha$), and the degrees of freedom ($N$-1). Confidence is defined as: if a large amount of CIs were constructed using repeated random sampling from a population, ($1\text{-}\alpha$) percent of those intervals would contain the true parameter (Montgomery, 2013).

In this study, confidence intervals of the population or true mean ($\mu$) were constructed to compare the CI range of the outputs to the base case outputs. This answers the question: are the base case outputs within the range of the expected central tendency of the outputs after the sources of uncertainty are introduced and repeated simulations are performed (i.e., within the range of true population means of the outputs) for a confidence level of ($1\text{-}\alpha$) percent?

Confidence intervals about the population mean ($\mu$) can be constructed using the standard normal distribution (i.e., $\mu$ = 0 and $\sigma^2$ =1) if the sample size is sufficiently large and the variance ($\sigma^2$) is known (Montgomery, 2013). Otherwise, the interval must be constructed using the sample variance ($S^2$) and the sample mean ($\bar{X}$) follows a student t-distribution rather than a normal distribution (Montgomery, 2013). Using the sample means from the first sub-model outputs ($z_{i,j,k,l,m,n}$) as an example, Equation 13 then becomes:

$$CI_{i,j,k,l,m,n}\colon\ \bar{X}_{i,j,k,l,m,n}\ \pm t\,\frac{s_{i,j,k,l,m,n}}{\sqrt{N=6}} \tag{14}$$

$t$ is the t-factor and can be obtained through different software or t-tables by specifying the degree of freedom ($N\text{-}1$) and significance level ($\alpha$) desired.

The use of the student t-statistic carries with it the normality assumption of the parameter for which the CI is being created. In this case, the sample means ($\bar{X}$) need to be normally distributed. Proving the normality assumption can be done using the Central Limit Theorem (CLT) if the sample sizes ($N$) are large enough (see more details in Section 3.3.5). CLT is not applicable for the for the outputs of the first sub-model ($z_{i,j,k,l,m,n}$) as the sample size ($N$) of 6 is too small. However, it can be argued that it applies for the outputs of the second and third sub-models as these have sample sizes of 24 and 168, respectively. The sample size of the outputs of the second model are under 30 which is often the recommended limit. However, moderate departures from normality do not seriously affect the result of a student t-test (Montgomery, 2013). Thus, a sample size of 24 is close enough to 30 that it should not affect the confidence interval analysis using the t-factors.

There are three options for the outputs of the first sub-model that do not meet the sample size requirement of the CLT. The first is to assume that they are approximately normally distributed and continue with the analysis. The second is to test for normality each individual supply chain over their six observations and continue with the analysis using only the outputs of the supply chains that are normally distributed according to the results of the normality tests. The third, is to use a non-parametric multiplier to create a CI. The last option is not desirable because the non-parametric tests are less powerful than parametric tests at the same sample sizes (Chin & Lee, 2008) and the sample sizes of the outputs of the other two sub-models are relatively small as well. Thus, the following is an exploration of the other two options.

First, the analysis was performed assuming that all the supply chains of the first sub-model follow a normal distribution. The CIs were calculated for all the outputs of the first ($z_{i,j,k,l,m,n}$), second ($t_{i,j,k,l,m,n}$), and third ($t_{j,k,d}$) sub-models. Then, the base case outputs for all three sub-models were compared against the ranges of their respective CIs. Finally, the percentage of base case outputs that were within the range of their respective CIs was calculated for each sub-model for all three CGE forecasts (2015, 2035, and 2035 with CPTPP). Figure 19 shows the results for three confidence levels 99%, 95%, and 90%.

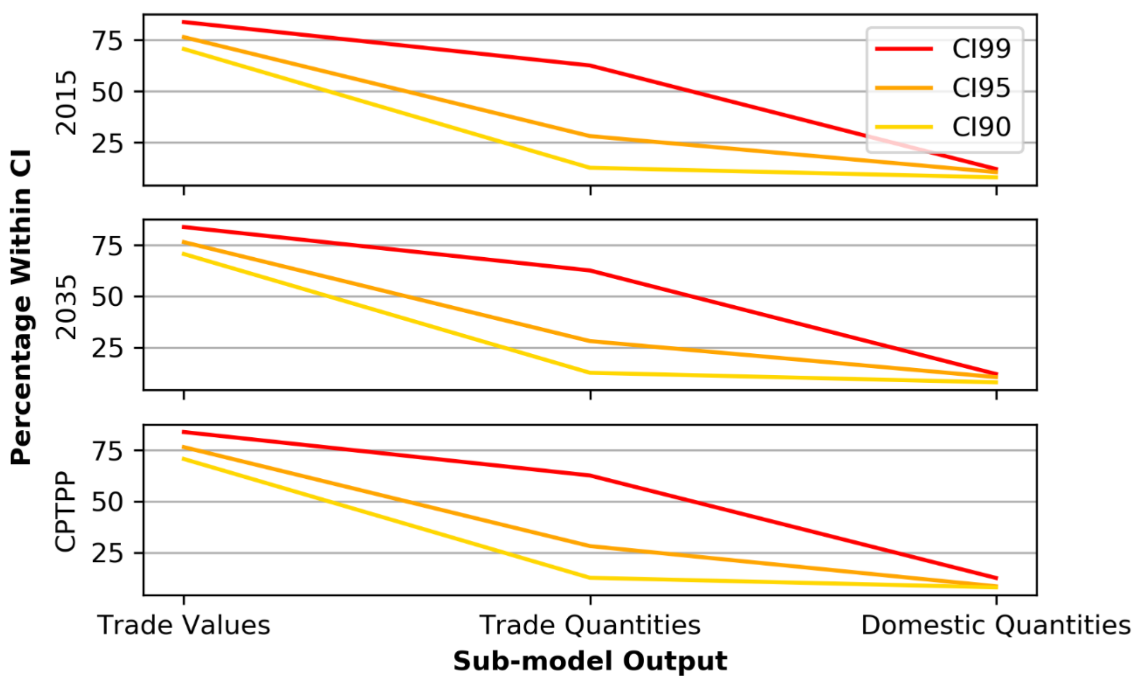


**Figure 19 Percentage of Base Case Outputs Within Mean CI**

Similar to the COV analysis (Figure 16), there is almost no difference between the results of each of the three CGE forecasts. Thus, the results for the 2015 forecast are presented an example in Figure 20.

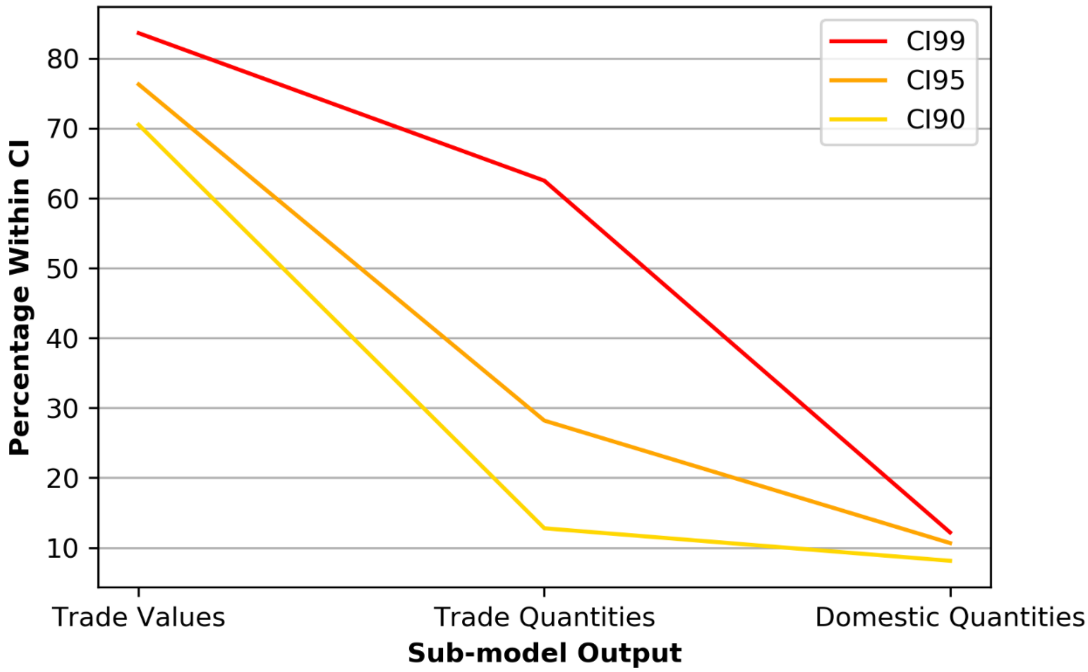


**Figure 20 Percentage of Base Case Outputs Within Mean CI (2015 Forecast)**

As expected, as confidence is increased, the number of base case outputs that fall within the CI range increases. This is because confidence intervals become narrower as the confidence level decreases (i.e., on repeated sampling from the population, less percentage of the total CIs will contain the true mean because they are narrower). The downward trend through the successive sub-models was also expected. Equation 14 shows that as *N* increases, the CIs become narrower since *N* is in the denominator. The sample size quadruples from the first sub-model to the second and is seven times larger than previously by the third sub-model. This explains why the trend is downwards as more variation (i.e., larger *N*) is introduced at each sub-model.

An unexpected result was the sharp decline in the percentage within CI90 and CI95 for the second sub-model. This decline was expected to resemble the trend for 99% confidence interval because the sample size increase from the first to the second sub-model is smaller than the sample size increase from the second to the third sub-model. Hence, it is expected to see a larger drop in the percentage of the base case outputs that fall within the CIs between the second to third sub-model than between the first to second sub-model. The only explanation for these observations is that the base case data happen to yield more extreme values for the second sub-model outputs that more often fell outside of the CIs at the confidence levels of 95% and 90%.

The normality test used on the outputs ($z_{i,j,k,l,m,n}$) of the first sub-model is the Shapiro-Wilk (SW) test, which is often recommended by researchers for various setups (Farrell & Rogers-Stewart, 2006; Keskin, 2006; Mendes & Pala, 2003; Mohd Razali & Bee Wah, 2011; Öztuna et al., 2006; Romão et al., 2010; Yap & Sim, 2011; Yazici & Yolacan, 2007). The null hypothesis ($H_0$) in this test is that the data are normally distributed. The test found not enough statistical evidence to reject the $H_0$ for only about 23% of all the outputs of the first sub-model. These outputs, which are then assumed normally distributed, were analyzed separately in Figure 21.

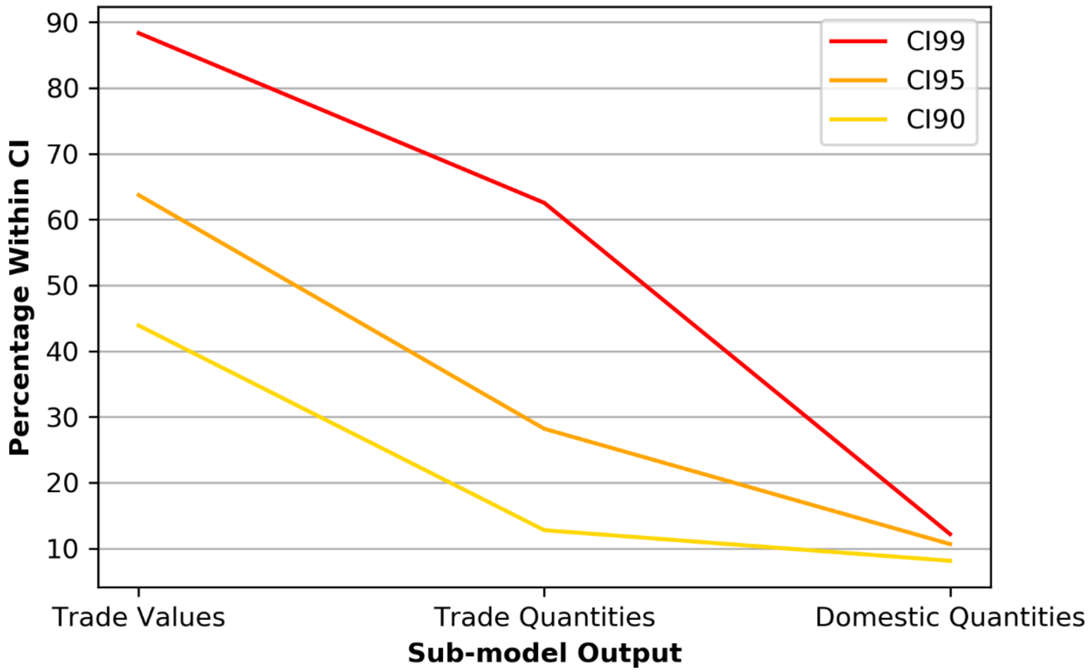


**Figure 21 Percentage of Base Case Outputs Within Mean CI After SW Test on Trade Values (2015 Forecast)**

The downward and steepness trends are similar to the results of the analysis using all the outputs of the first sub-model (i.e., assuming normality for all results). However, there is a noticeable difference between results for different confidence levels. In Figure 20, the percentage of base case outputs that fell within the range of the CIs did not go below 70%, even at the 90% confidence level. Figure 21 shows that at the 95% confidence level, the percentage drops to about 64%. Then it drops further to about 44% at the 90% confidence level. If this study only conducted the analysis using a confidence level of 95% (which is typical), the conclusions about the outputs of the first sub-model would be very different depending on whether the assumption of normality was made or how it was tested. This highlights the importance of understanding the assumption of normality and choosing the correct procedure for statistical analysis. Finally, at the 99% confidence level, there is very little difference between the normality tested results and the assumed normality results.

The overall conclusion of this CI analysis is however the same for both the assumed normality results and the ones obtained using the SW normality test. Overall, the percentages of base case outputs that are within the ranges of the CIs for the 95% confidence level are very low. In both cases, the percentage start at acceptable values but rapidly drops below 30% by the second sub-model and then just above 10% by the third sub-model at the 95% confidence level. This means that only about 10% of the base case outputs ($t_{j,k,d}$) for the third sub-model fall within the range of the CIs at the 95% confidence level. This suggests that if all the available data are used (i.e., the true population of the outputs is simulated), the freight model will yield statistically different mean values than the base case values. However, these results pertain specifically to the illustrative base case, other base cases may fall closer to or further from the population mean outputs.

## 4.2. Aggregated Outputs

In the preliminary study, three types of aggregated results from the base case were provided. The first set of results were aggregations over three gateways (defined below). The second set of results were aggregations over all supply chain characteristics (*i*,*j*,*k*,*l*,*m*) except for ports of entry (*n*) in order to identify the top ten most affected ports by the absolute increases in yearly tonnage of exports. The last set of results were the aggregated domestic export trade growth results. More detail is provided in the sections below. The gateways, ports of clearance, and provincial/territorial boundaries are presented in Figure 22.

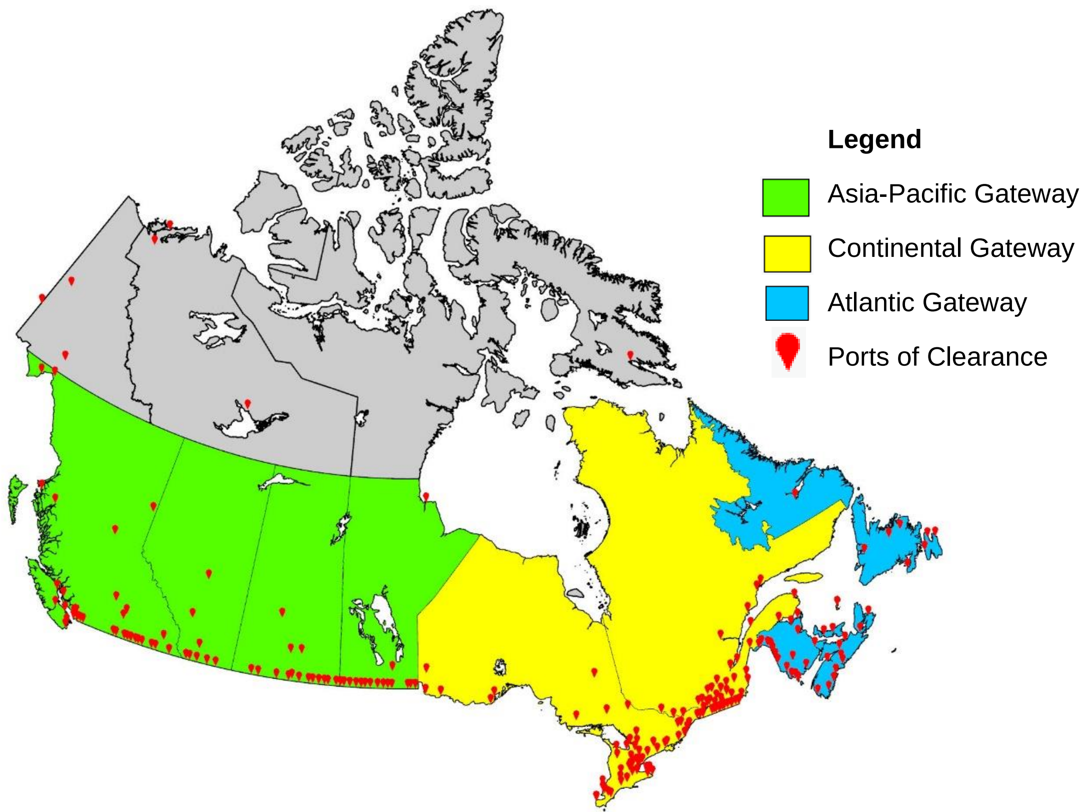


**Figure 22 Gateways and Ports of Clearance**

The aggregated outputs were presented in the form of tables. For each type of result, two tables were prepared. The first table showed the growth in exports over the study period (2015-2035) due to forecasted trade growth alone. The second table showed the additional export impact introduced into the economy by forecasting the effects of the CPTPP policy shocks over the study period.

The analysis procedure applied to the aggregated outputs similar to the one applied to the disaggregated outputs. First, descriptive statistics are calculated, then confidence intervals are created, and finally, the percentage of base case outputs that fall within the CIs are obtained. The results are presented using similar tables to the preliminary study for ease of direct comparison of conclusions. Consequently, the major conclusions of the base case study are reassessed using mean data and compared to the base case conclusion to discern similarities and discrepancies.

The analysis performed on the port rankings is different from the analyses performed on the disaggregate data. Rank measurements are used in addition to the descriptive statistics to assess the variation on the top ten results.

Note that a high level of detail for the explanations of some of the procedures is not provided below as they are, in essence, the same as the descriptions in Section 4.1.

### 4.2.1. Gateway Summaries

There were three gateways defined in the base case study. The Asia-Pacific gateway includes the trade infrastructure in the provinces of British Columbia, Alberta, Saskatchewan, and Manitoba. The Continental gateway encompasses the trade infrastructure of Ontario and Quebec. Lastly, the infrastructure of the Canada's Maritime provinces (Nova Scotia, New Brunswick, Prince Edward Island, and Newfoundland and Labrador) belongs to the Atlantic gateway.

The repeated simulations yielded 24 unique values for each summary table (i.e., 6 x 4). Essentially, 24 tables depicting the results of the forecasted export trade growth over 2015-2035 were created as well as 24 tables showing the additional impacts of the CPTPP on exports. The gateway analyses are only affected by the variation introduced on the first and second sub-models as they are concerned with international trade quantities ($t_{i,j,k,l,m,n}$) measured in yearly tonnage. Domestic supply chains are not introduced in the gateway analysis.

Descriptive statistics were calculated for the results of the repeated simulations regarding export trade growth between 2015-2035 without the CPTPP. Table 15 shows the means of the 24 observations (tables) created through repeated simulations. Table 16 shows the corresponding COVs. The colour coding on this table depicts the magnitude of dispersion for each point on the table with red being the highest and green being the lowest. COV values over 1 are considered high variance and are shown in different shades of reds. Conversely, dispersion values under 1 are considered low variance and are depicted in a range of yellow to green colours.

Most of the same major findings on the base case study (Table 17) can be concluded using the mean data (Table 15) but some cannot. First, the largest relative growth in exports on average was observed on the Atlantic gateway to CPTPP countries. However, the relative growth observed in the base case is larger (106%) than the mean outputs (66%) making the conclusion more obvious. Second, the largest absolute growth in exports is from the Atlantic gateway to the rest-of-the-world (ROW) countries on the base case but it is from the Continental gateway to ROW on average. Third, double digit growth is forecasted over the study period for almost all of Canada's international transportation modes on average and in the base case. Last, the largest relative and absolute growth are by air and water respectively on average and for the base case. However, once again, the values for the base case are higher than the mean values. Overall, most major findings were the same, meaning that, although many aspects of this model exhibit high variance in the disaggregated results, the conclusions of the base case are mostly in line with the mean major conclusions for major gateways after findings are aggregated.

### Table 15 Mean Values for Forecasted Export Tonnage Growth - Gateway Summary

| | Water | | Air | | Road | | Rail | | Other | | Total | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Gateway** | **Tonnes** | **%** | **Tonnes** | **%** | **Tonnes** | **%** | **Tonnes** | **%** | **Tonnes** | **%** | **Tonnes** | **%** |
| **Asia-Pacific, outbound to CPTPP** | 4,345,219 | 18 | 326,082 | 49 | 74,413 | 37 | 189,870 | 34 | 730 | 58 | 4,936,313 | 20 |
| **Asia-Pacific, outbound to ROW** | 49,825,882 | 50 | 340,402 | 44 | 1,408,454 | 9 | 2,174,181 | 13 | 2,182,283 | 3 | 55,931,202 | 27 |
| **Continental, outbound to CPTPP** | 1,005,116 | 26 | 172,147 | 45 | 292,456 | 57 | 616,338 | 54 | 1,033 | 61 | 2,087,090 | 36 |
| **Continental, outbound to ROW** | 53,384,451 | 65 | 1,420,239 | 52 | 5,938,553 | 10 | 3,689,745 | 13 | 285,459 | 3 | 64,718,447 | 35 |
| **Atlantic, outbound to CPTPP** | 4,150,785 | 66 | 3,368 | 36 | 2,367 | 29 | 434 | 70 | 98 | 49 | 4,157,052 | 66 |
| **Atlantic, outbound to ROW** | 37,876,934 | 33 | 30,812 | 31 | 170,828 | 9 | 39,778 | 10 | 68,166 | 5 | 38,186,518 | 32 |
| **Total, Outbound (Exports)** | 150,588,387 | 47 | 2,293,051 | 50 | 7,887,071 | 10 | 6,710,344 | 14 | 2,537,769 | 3 | 170,016,622 | 31 |

### Table 16 COVs for Forecasted Export Tonnage Growth - Gateway Summary

| | Water | | Air | | Road | | Rail | | Other | | Total | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Gateway** | **Tonnes** | **%** | **Tonnes** | **%** | **Tonnes** | **%** | **Tonnes** | **%** | **Tonnes** | **%** | **Tonnes** | **%** |
| **Asia-Pacific, outbound to CPTPP** | 0.045 | 0.041 | 1.355 | 0.394 | 0.434 | 0.108 | 0.269 | 0.096 | 1.461 | 0.321 | 0.092 | 0.088 |
| **Asia-Pacific, outbound to ROW** | 0.109 | 0.265 | 0.364 | 0.334 | 0.096 | 0.049 | 0.071 | 0.070 | 0.144 | 0.102 | 0.097 | 0.214 |
| **Continental, outbound to CPTPP** | 0.877 | 0.401 | 0.256 | 0.068 | 0.153 | 0.053 | 0.178 | 0.124 | 1.000 | 0.138 | 0.435 | 0.205 |
| **Continental, outbound to ROW** | 0.219 | 0.099 | 0.327 | 0.102 | 0.139 | 0.069 | 0.065 | 0.044 | 0.242 | 0.050 | 0.182 | 0.096 |
| **Atlantic, outbound to CPTPP** | 1.656 | 0.424 | 1.775 | 0.460 | 0.807 | 0.383 | 0.784 | 0.196 | 1.344 | 0.524 | 1.654 | 0.426 |
| **Atlantic, outbound to ROW** | 0.825 | 0.266 | 1.410 | 0.330 | 0.095 | 0.076 | 0.448 | 0.292 | 0.308 | 0.350 | 0.818 | 0.272 |
| **Total, Outbound (Exports)** | 0.279 | 0.104 | 0.300 | 0.157 | 0.108 | 0.061 | 0.065 | 0.049 | 0.147 | 0.087 | 0.250 | 0.087 |

### Table 17 Base Case Values for Forecasted Export Tonnage Growth - Gateway Summary

| | Water | | Air | | Road | | Rail | | Other | | Total | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Gateway** | **Tonnes** | **%** | **Tonnes** | **%** | **Tonnes** | **%** | **Tonnes** | **%** | **Tonnes** | **%** | **Tonnes** | **%** |
| **Asia-Pacific, outbound to CPTPP** | 4,467,562 | 19 | 1,742,885 | 95 | 54,415 | 39 | 171,755 | 35 | 94 | 40 | 6,436,711 | 25 |
| **Asia-Pacific, outbound to ROW** | 52,120,795 | 38 | 301,027 | 50 | 1,687,842 | 8 | 2,240,270 | 12 | 2,345,448 | 3 | 58,695,381 | 22 |
| **Continental, outbound to TPP** | 3,885,784 | 52 | 124,631 | 42 | 316,226 | 59 | 686,841 | 60 | 2,526 | 74 | 5,016,008 | 53 |
| **Continental, outbound to ROW** | 68,040,143 | 58 | 966,772 | 58 | 5,982,323 | 10 | 3,690,373 | 12 | 356,474 | 3 | 79,036,086 | 35 |
| **Atlantic, outbound to CPTPP** | 17,200,845 | 106 | 26,095 | 77 | 467 | 26 | 786 | 69 | 22 | 12 | 17,228,214 | 106 |
| **Atlantic, outbound to ROW** | 108,004,056 | 45 | 7,755 | 26 | 159,053 | 9 | 35,425 | 9 | 65,216 | 3 | 108,271,505 | 45 |
| **Total, Outbound (Exports)** | 253,719,184 | 47 | 3,169,165 | 71 | 8,200,325 | 10 | 6,825,450 | 13 | 2,769,781 | 3 | 274,683,906 | 35 |

The COVs for each gateway summary value can be seen in Table 16. Most of the values exhibit low variances (COV<1). For example, all the relative growth values have dispersion values under 0.5 except for the values of the Atlantic gateways outbound to CPTPP countries using other mode of transportation (~0.52). This gateway also exhibited high variance of the absolute growth in yearly tonnage results more often than the other gateways and it had the highest COV value (~1.77) on the table. Although there are a few instances of high variance, the values are still relatively small as expected. The gateway summary analysis is highly aggregated which lowers the dispersion in the data.

The CIs were created for all the values in the table as well. Table 17 shows the base case values with colour coding depicting the values that fell within their respective 95% CIs (green) and the values that did not (red). The percentage of values that were within the CI was calculated for confidence levels of 99%, 95%, and 90%. The results were 29.8% 20.2% and 17.9% for the 99%, 95%, and 90% CIs respectively. These percentages are low meaning that statistically, the base case aggregated outputs are not generally within the expected values on average for 99%, 95%, and 90% levels of confidence.

Although, the dispersion is relatively small, there was not enough statistical evidence to prove that about 70% of the base case values were within the expected range of the central tendency at the 99%, 95% and 90% confidence levels. The range or size of CIs lowers as dispersion lowers meaning that they get narrower. This effect is seen in distributions with less pronounced extremes or tails due to the lower dispersion. Ultimately, the base case data seem to yield values that are closer to the extremes of the sample mean distribution based on the CIs created through repeated simulation. However, it was also shown that due to the low dispersion of these results, similar major conclusions can be drawn from the freight model after using point (base case) data and the repeated simulation outputs for summaries of gateways.

Table 18 and Figure 23 further illustrate the point above as examples. Table 18 shows an analysis of all the simulated outputs for exports through the Asia-Pacific gateway outbound to CPTPP signatories via water mode using absolute and relative errors (with the expected value being the sample mean).

Table 18 Asia-Pacific Gateway Exports outbound to CPTPP Countries (Water)

| Simulation Setting | Value [tonnes] | Abs. Error | Rel. Error |
|---|---|---|---|
| 2010 CBSA, 5_digit | 4,389,039 | 43,820 | 1.01 |
| 2011 CBSA, 5_digit | 4,476,427 | 131,209 | 3.02 |
| 2012 CBSA, 5_digit | 4,630,654 | 285,436 | 6.57 |
| 2013 CBSA, 5_digit | 4,485,372 | 140,153 | 3.23 |
| 2014 CBSA, 5_digit | 4,360,683 | 15,464 | 0.36 |
| 2015 CBSA, 5_digit | 4,467,562 | 122,344 | 2.82 |
| 2010 CBSA, 4_digit | 4,180,517 | 164,702 | 3.79 |
| 2011 CBSA, 3_digit | 4,119,557 | 225,661 | 5.19 |
| 2012 CBSA, 2_digit | 4,240,844 | 104,374 | 2.40 |
| 2013 CBSA, 4_digit | 4,249,153 | 96,066 | 2.21 |
| 2014 CBSA, 3_digit | 4,225,931 | 119,288 | 2.75 |
| 2015 CBSA, 2_digit | 4,514,013 | 168,794 | 3.88 |
| 2010 CBSA, 4_digit | 4,307,891 | 37,327 | 0.86 |
| 2011 CBSA, 3_digit | 4,339,072 | 6,147 | 0.14 |
| 2012 CBSA, 2_digit | 4,775,116 | 429,898 | 9.89 |
| 2013 CBSA, 4_digit | 4,150,886 | 194,333 | 4.47 |
| 2014 CBSA, 3_digit | 4,174,771 | 170,447 | 3.92 |
| 2015 CBSA, 2_digit | 4,587,785 | 242,566 | 5.58 |
| 2010 CBSA, 4_digit | 4,066,489 | 278,729 | 6.41 |
| 2011 CBSA, 3_digit | 4,106,590 | 238,628 | 5.49 |
| 2012 CBSA, 2_digit | 4,595,107 | 249,889 | 5.75 |
| 2013 CBSA, 4_digit | 4,136,104 | 209,114 | 4.81 |
| 2014 CBSA, 3_digit | 4,150,572 | 194,647 | 4.48 |
| 2015 CBSA, 2_digit | 4,555,110 | 209,891 | 4.83 |
| **Mean [tonnes]** | 4,345,219 | - | - |
| **Standard Deviation [tonnes]** | 194,829 | - | - |
| **95% CI [tonnes]** | 4,262,950 - 4,427,490 | | - |

The base case output is highlighted in yellow. The outputs of the simulation settings that are highlighted in green are the ones that fall within the confidence interval about the population mean. These values have relative errors of less than approximately 1%. Any other simulation output that differs from the sample mean by more than about 1% is not within the expected range of the true population mean at the 95% confidence level. This is expected as the COV indicates that the standard deviation is small for this output which makes the CI narrower. The base case output has a relative error of less than 3%. This small relative error also explains why similar conclusions can be drawn using the base case output and the mean output, despite the difference not being small enough to fall within the expected range of the true population mean at the 95% confidence level.

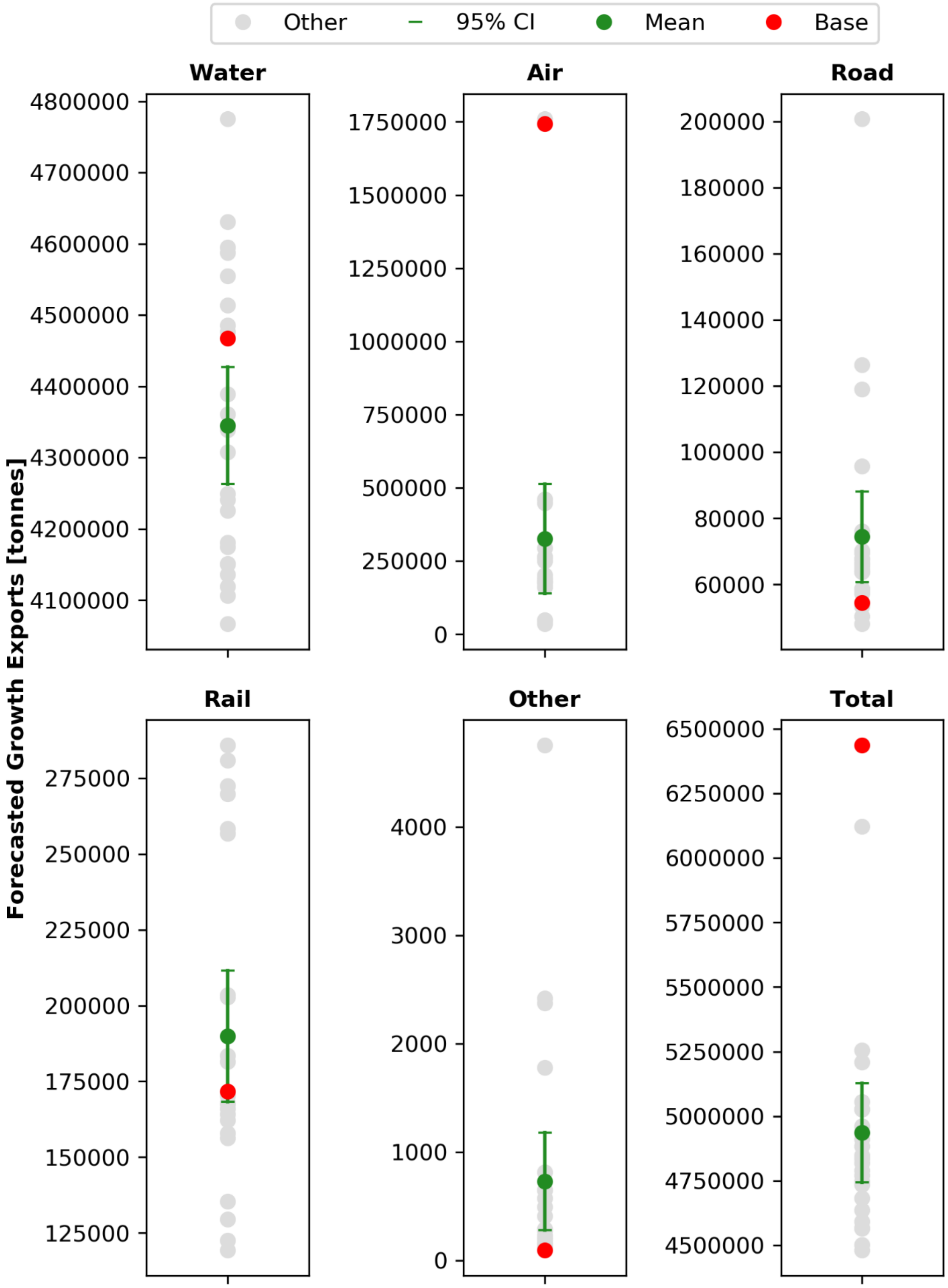


**Figure 23 Asia-Pacific Gateway Exports outbound to CPTPP Countries (All Modes)**

Figure 23 shows the confidence intervals (confidence level = 95%), the mean (in green), and the base case outputs (in red) for the exports through the Asia-Pacific gateway outbound to CPTPP signatories via all modes and their total over all modes. The other makers on the figure are the other simulated observations (in light grey). Essentially, this figure is a different visual representation of the absolute export results on the first rows of Table 15 and Table 17. As in Table 17, the only value that falls within the CI at the 95% confidence level is the export value of the rail mode. The base case values for the mode of air and the total are far outside of the CI range. This makes sense since rail is a highly utilized mode for the transportation of commodities meaning that there is likely more consistency in shipments via rail from year to year (large amounts of commodities are shipped year to year); and the opposite is true for the air mode where any increase between years can be perceived as a large fluctuation since it is likely less consistently utilized. This is also confirmed looking at their respective COVs (see Table 16) where rail exhibits low variances and air exhibits high variances.

Additionally, Figure 23 shows that there are observed values that are separated from the bulk of the results. For example, the base case value for the mode of air is significantly larger than other sets of results. This indicates there was a significant uptake in the exports transported via air in the last year of data available for the CBSA records for the Asia-Pacific gateway aggregation. It is hard to discern whether this is a trend that continues forward (after 2015) or if this year is an outlier because there are no data available for later years.  Moreover, the supply chains of the presumptive outliers may not be the same for all results. For example, the base case (in red) is within the bulk of the results for the modes of water, road, rail and other, but it is far outside of the bulk of the runs for the modes of air and total. This makes it difficult to choose a supply chain as an outlier since the researcher would have to choose which output to use in identifying the outlier, since the apparent outlier supply chains likely differ among the simulated results of the outputs.

The same analysis was repeated for the gateway summary of additional export impacts of implementing the CPTPP from 2015-2035. Table 19, Table 20, and Table 21 show the results.

**Table 19 Mean Values for Additional CPTPP Export Tonnage Impact - Gateway Summary**

| | Water | Air | Road | Rail | Other | Total |
|---|---|---|---|---|---|---|
| **Gateway** | **Tonnes** | **Tonnes** | **Tonnes** | **Tonnes** | **Tonnes** | **Tonnes** |
| **Asia-Pacific, outbound to CPTPP** | 1,090,177 | 87,827 | 4,368 | -5,441 | 57 | 1,176,987 |
| **Asia-Pacific, outbound to ROW** | -343,321 | -3,902 | -52,439 | -36,819 | -33,595 | -470,076 |
| **Continental, outbound to CPTPP** | 29,977 | 21,802 | 5,045 | -8,338 | 12 | 48,498 |
| **Continental, outbound to ROW** | -193,591 | -16,644 | -120,934 | -58,886 | -4,476 | -394,530 |
| **Atlantic, outbound to CPTPP** | 10,887 | 411 | 787 | 19 | 36 | 12,140 |
| **Atlantic, outbound to ROW** | -125,037 | -396 | -5,301 | -881 | -1,302 | -132,917 |
| **Total, Outbound (Exports)** | 469,090 | 89,098 | -168,474 | -110,346 | -39,267 | 240,101 |

**Table 20 COVs for Additional CPTPP Export Tonnage Impact - Gateway Summary**

| | Water | Air | Road | Rail | Other | Total |
|---|---|---|---|---|---|---|
| **Gateway** | **[-]** | **[-]** | **[-]** | **[-]** | **[-]** | **[-]** |
| **Asia-Pacific, outbound to CPTPP** | 0.134 | 0.429 | 1.028 | 0.294 | 0.801 | 0.103 |
| **Asia-Pacific, outbound to ROW** | 0.122 | 0.175 | 0.089 | 0.154 | 0.146 | 0.112 |
| **Continental, outbound to CPTPP** | 1.009 | 0.290 | 0.884 | 0.742 | 2.192 | 0.625 |
| **Continental, outbound to ROW** | 0.176 | 0.463 | 0.147 | 0.094 | 0.262 | 0.106 |
| **Atlantic, outbound to CPTPP** | 1.118 | 0.506 | 1.146 | 1.671 | 1.480 | 1.012 |
| **Atlantic, outbound to ROW** | 0.609 | 0.692 | 0.123 | 0.195 | 0.278 | 0.570 |
| **Total, Outbound (Exports)** | 0.146 | 0.416 | 0.070 | 0.122 | 0.159 | 0.242 |

**Table 21 Base Case for Additional CPTPP Export Tonnage Impact - Gateway Summary**

| | Water | Air | Road | Rail | Other | Total |
|---|---|---|---|---|---|---|
| **Gateway** | **Tonnes** | **Tonnes** | **Tonnes** | **Tonnes** | **Tonnes** | **Tonnes** |
| **Asia-Pacific, outbound to CPTPP** | 1,195,368 | 118,723 | -2,143 | -4,320 | 17 | 1,307,647 |
| **Asia-Pacific, outbound to ROW** | -397,467 | -3,446 | -61,918 | -43,635 | -36,292 | -542,758 |
| **Continental, outbound to CPTPP** | 127,571 | 17,774 | 4,525 | -11,866 | -25 | 137,979 |
| **Continental, outbound to ROW** | -234,527 | -7,564 | -108,778 | -64,796 | -5,196 | -420,862 |
| **Atlantic, outbound to CPTPP** | 13,215 | 185 | -9 | 88 | 1 | 13,479 |
| **Atlantic, outbound to ROW** | -290,038 | -147 | -4,825 | -906 | -1,267 | -297,183 |
| **Total, Outbound (Exports)** | 414,122 | 125,525 | -173,149 | -125,434 | -42,762 | 198,302 |

The CI analysis yielded lower percentages for the additional export results than the forecasted growth results. The results were 21.4%, 14.3% and 11.9% for the 99%, 95%, and 90% confidence levels, respectively. At the 95% confidence level, there was not enough statistical evidence to prove that ~88% of the base case results are within the expected range of the repeated simulations on average.

The exact same major observations of the base case can be concluded using the mean results. The overall impacts of implementing the CPTPP are relatively small when compared to those due to trade growth, with total net increases in exports of 240 thousand tonnes per year by 2035. This number is smaller in the base case, 198 thousand tonnes per year by 2035, but the same conclusion remains. As in the base case, the largest impacts were observed in the Asia-Pacific gateway, increasing by over a million tonnes per year in exports (about the same as the base case value) shipped by water to CPTPP countries. In both the base case and the mean values, the magnitude of the total CPTPP impacts show a clear relation to the gateway's proximity to the CPTPP countries, with the largest being at the Asia-Pacific (nearest), then the Continental, and lastly the Atlantic (furthest).

The dispersion of the results is low. The majority of the COVs indicated low variance on Table 20. Only the COV of the Continental gateway additional export impacts outbound to CPTPP countries via other mode is over 1.7. The Atlantic gateway additional export impacts outbound to CPTPP countries exhibited more instances of high variance over all the modes.

As in the forecasted export growth results, the findings are reasonable. The low dispersion of the data, due to their highly aggregated nature, explains the ability to draw similar conclusions using both the base case results and the mean results although the CI analysis yielded low percentages. In these results, the base case data also seem to yield results at the 99%, 95% and 90% confidence levels, that did not present enough statistical evidence to conclude that they are within the expected range of the central tendency of the simulated results, meaning that the base case data tend to yield more extreme results (i.e., results closer to the tails of the distribution).

#### 4.2.2. Ports of Clearance Top Ten

In the preliminary study, the results were aggregated by port of clearance and the top ten ports were presented (see Table 22). The top ten ports were selected based on the largest absolute impacts measured in yearly tonnage from 2015 to 2035 for both the forecasted export growth results and the additional CPTPP export impact results. The total number of ports examined was 246.

**Table 22 Forecasted Export Growth Top Ports of Clearance – Base Case Results**

| Port of Clearance | Province | Gateway | Tonnes | % |
|---|---|---|---|---|
| St. Johns | Newfoundland/Lab | Atlantic | 73,139,564 | 71 |
| Vancouver - Marine and Rail | British Columbia | Asia-Pacific | 48,248,095 | 37 |
| Montréal - Main Long Room | Quebec | Continental | 34,267,760 | 85 |
| Sept-Îles | Quebec | Continental | 33,368,912 | 67 |
| St. Stephen | New Brunswick | Atlantic | 28,965,628 | 73 |
| Halifax | Nova Scotia | Atlantic | 18,263,551 | 46 |
| Prince Rupert | British Columbia | Asia-Pacific | 3,965,453 | 49 |
| Port Hawkesbury | Nova Scotia | Atlantic | 3,439,787 | 6 |
| Nanaimo | British Columbia | Asia-Pacific | 2,668,910 | 85 |
| Sarnia | Ontario | Continental | 2,495,096 | 11 |

The simulation created 24 set of results for all 246 ports of clearance for both the forecasted export growth results and the addition CPTPP export impact results. The total observations are 24 and not 168 for the same reason as the gateway summary analyses discussed in Section 4.2.1: the third sub-model (domestic quantities) is not used. These sets were used to calculate descriptive statistic measures. Table 23 shows the top ten ports of clearance according to their mean forecasted export growth results from 2015-2035 measured in yearly tonnage. The table also shows their respective mean relative growth results (%) and their COVs. The resulting dispersion of the top ten results indicates mostly low variance as expected of highly aggregate results.

**Table 23 Forecasted Export Growth Top Ports of Clearance - Mean Results**

| Port of Clearance | Province | Gateway | Tonnes | | % | |
|---|---|---|---|---|---|---|
| | | | Avg. | COV | Avg. | COV |
| Vancouver - Marine and Rail | British Columbia | Asia-Pacific | 44,811,919 | 0.10 | 45 | 0.19 |
| Sept-Îles | Quebec | Continental | 40,817,257 | 0.28 | 88 | 0.15 |
| St. Johns | Newfoundland/Lab | Atlantic | 24,326,502 | 1.03 | 65 | 0.11 |
| Montréal - Main Long Room | Quebec | Continental | 9,442,516 | 0.81 | 47 | 0.29 |
| Halifax | Nova Scotia | Atlantic | 6,637,938 | 0.71 | 50 | 0.18 |
| St. Stephen | New Brunswick | Atlantic | 5,757,590 | 1.46 | 37 | 0.85 |
| Prince Rupert | British Columbia | Asia-Pacific | 4,444,807 | 0.17 | 47 | 0.22 |
| Port Hawkesbury | Nova Scotia | Atlantic | 2,658,748 | 0.84 | 8 | 0.52 |
| Nanaimo | British Columbia | Asia-Pacific | 2,617,392 | 0.27 | 77 | 0.05 |
| Sarnia | Ontario | Continental | 2,355,496 | 0.05 | 11 | 0.03 |

A visual comparison of Table 22 and Table 23 shows that the ports on both top tens are the same but in different rankings. For example, the Vancouver – Marine and Rail port of clearance ranked first on average, whereas the St. Johns port of clearance ranked first on the base case results. This observation prompted an examination of the ranked positions of the ports in the top for all the repeated simulation results.

Figure 24 shows the results of this examination. For al 24 simulation runs, a total of 18 unique ports of clearance were ranked in the top ten. The percentage of total observations (24) where a port ranked in a particular place (from 1$^{st}$ to 10$^{th}$) was calculated for all 18 ports.

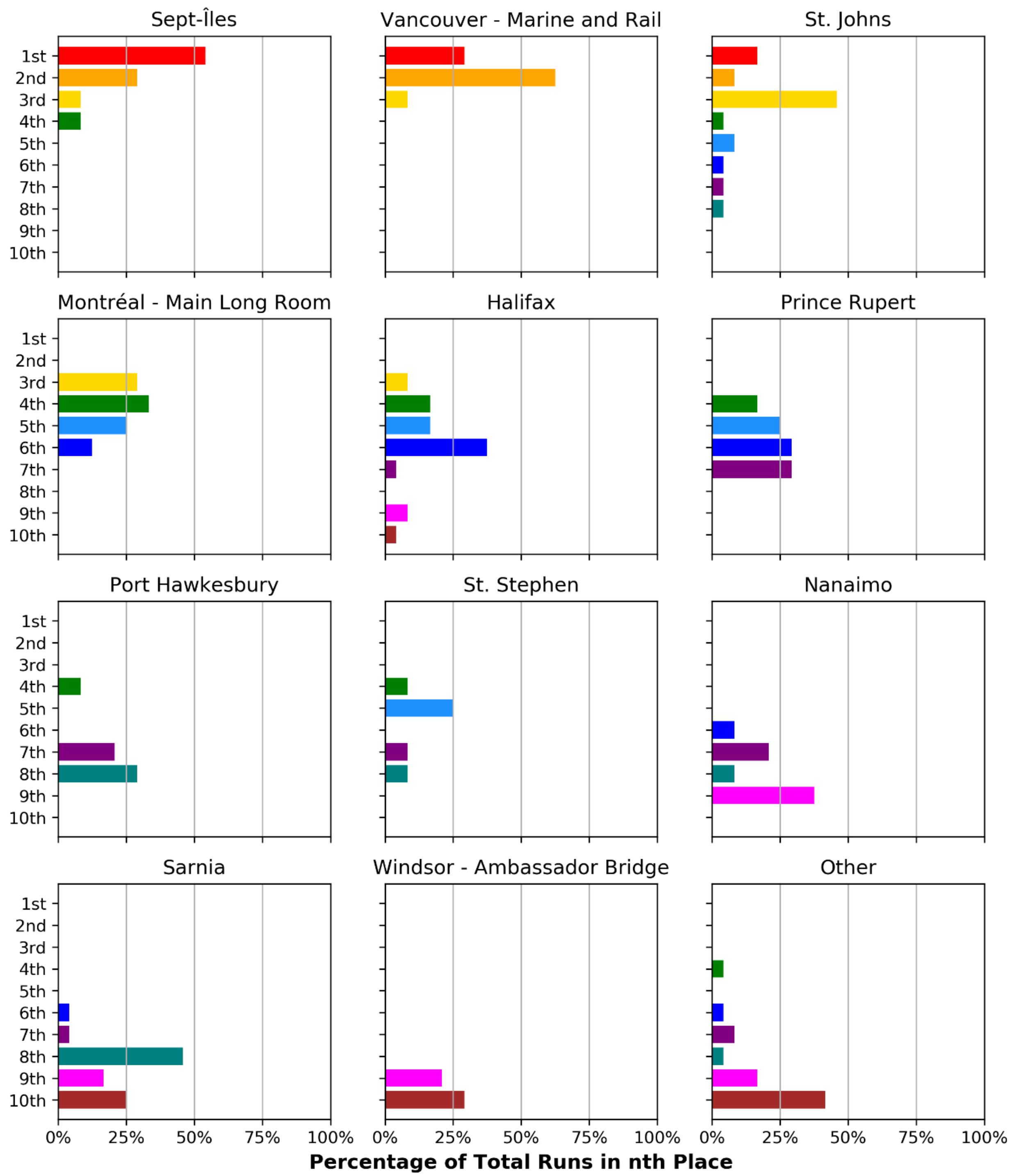


**Figure 24 Forecasted Export Growth Top Ports of Clearance – All Ports in Top Ten**

Figure 24 presents 11 ports plus an aggregation of remaining ports in the "other" category. The selection of the ports in the other category was based on cumulative percentages. The 11 ports presented on the figure account for over 90% of the total observations (24 runs by 10 ranked ports). The other category includes the ports: Quebec, St. Andrews, Fort Erie, Ontario, Conerbrook, Vancouver – Main Long Room and Toronto Pearson International Airport (<8% of total observations).

The most variation in rankings is observed in the mid-ranking places. The first and second places were occupied by the same three ports: Sept-Îles, Vancouver – Marine and Rail and St. Johns. An interesting finding is the percentage of time that the port of Sept-Îles occupies first place is higher than that of the Vancouver – Marine and Rail port which is ranked first on average. This means that the values of the forecasted export growths measured in yearly tonnes (2015-2035) for Sept-Îles are on average smaller than the values for Vancouver – Marine and Rail but manage to exceed the latter port for first place more often. Another interesting finding is that not all top ten lists contain the same ports. This observation prompted another analysis using rank error measures.

The utilized rank error method (Xaykongsa, 2021) quantifies the level of similarity between ranking methodologies. In this thesis, the ranking methodologies studied are defined as one simulation run. Consequently, the rank error method was used to quantify the level of similarity between the top ten rankings created by each simulation run (total 24). This method contains multiple measures. However, for this thesis, the relative rank error ($RRE_n$) and the relative rank error weighted average ($RRE_{wa}$) are used. The $RRE_n$ percentage represents the fraction of the top $n$ ranked ports of clearance that would be expected to be different between simulation run results. The $RRE_{wa}$ is a weighted average of the $RRE_n$ over the total possible number of lists $N$. The top $n$ relative rank error ($RRE_n$) is computed using the following:

$$RRE_n = \frac{n-m}{n} \tag{15}$$

where $m$ is the number of sites that are included by all simulation runs in the top $n$ ranked ports of clearance. Then, the equation below was used to calculate the weighted average of the relative rank errors:

$$RRE_{wa} = \frac{\sum_{n=1}^{N} \frac{RRE_n}{n}}{\sum_{n=1}^{N} \frac{1}{n}} \tag{16}$$

Using the 24 simulation results, the calculated $RRE_{wa}$ was 78.4%. Six ports out of the top ten are expected to be different ($RRE_{10}$ = 60%), when the ports are ranked using the freight model after introducing uncertainty in the supply chain shares (6 years of CBSA data) and in the value-weight ratios (4 aggregation schemes of SCTG codes). Table 24 shows the results of the $RRE_n$ for each value of $n$. The high $RRE_{wa}$ suggests that, regardless of the small dispersion of the ports ranked top ten using the means, there is significant fluctuation between the simulation runs on the ports that are selected as top ten. This is in line with Figure 24, as this visual representation of the variation present in the ports of clearance ranked top ten, for different simulation runs, also suggests that they vary widely. When the disaggregated simulation results are aggregated by ports of clearance and then averaged, the ranked top ten list is very similar to the base case (i.e., same ports on both lists but with differences in the places they occupy). However, the $RRE_{wa}$ reveals that, if the results are not averaged but different base case scenarios are selected individually, the top 10 rankings obtained are going to be very different on average between different scenarios. Thus, the results imply the importance of considerations selecting base cases for these aggregated port of clearance results if all available data are not used.

**Table 24 Rank Error Results for the Forecasted Export Growth Top Ports of Clearance**

| ***n*** | ***m*** | ***RREn*** |
|---|---|---|
| 1 | 0 | 1.00 |
| 2 | 0 | 1.00 |
| 3 | 1 | 0.67 |
| 4 | 2 | 0.50 |
| 5 | 2 | 0.60 |
| 6 | 3 | 0.50 |
| 7 | 4 | 0.43 |
| 8 | 4 | 0.50 |
| 9 | 4 | 0.56 |
| 10 | 4 | 0.60 |
| | ***RREwa*** | **78.39%** |

Finally, a similar conclusion to the major conclusion presented on the base case study can be observed on the mean data as well. For both ranked lists, the top two largest absolute impacts were seen on the ports of St. John and Vancouver – Marine and Rail. This is in line with other results as these highly aggregated results exhibit low variance in terms of their values despite the high $RRE_{wa}$.

The same three analyses were conducted for the results of the repeated simulations for additional export impacts after implementing the CPTPP. Table 25 shows the results for the base case and Table 26 shows the top ten ports according to the mean of the 24 runs. Figure 25 shows the fraction of total observations that a port occupies a particular ranked place.

The visual comparison between Table 25 and Table 26 yielded different observations for this set of results. Unlike in the forecasted growth results, there are six ports of clearance that are unique to either ranked list. The other 14 ports that are common in both tables vary in their ranked places as expected. Additionally, Table 26 has more instances where the COVs indicate high variance, but most of the values are low variance.

**Table 25 Additional CPTPP Export Impact Top Ports of Clearance – Base Case Results**

| Port of Clearance | Province | Gateway | Tonnes | $1,000 |
|---|---|---|---|---|
| Vancouver - Marine and Rail | British Columbia | Asia-Pacific | ▲ 822,865 | ▲ 1,050,063 |
| Calgary | Alberta | Asia-Pacific | ▲ 77,082 | ▲ 31,573 |
| Vancouver - Int. Airport | British Columbia | Asia-Pacific | ▲ 38,028 | ▲ 128,799 |
| Montréal - Main Long Room | Quebec | Continental | ▲ 21,918 | ▼ -42,563 |
| Port Alberni | British Columbia | Asia-Pacific | ▲ 14,707 | ▲ 4,857 |
| Niagara Falls | Ontario | Continental | ▲ 5,680 | ▲ 44,420 |
| Toronto - Pearson Int. Airport | Ontario | Continental | ▲ 5,675 | ▲ 48,056 |
| Montréal - Trudeau Int. Airport | Quebec | Continental | ▲ 4,264 | ▲ 84,357 |
| Kitimat | British Columbia | Asia-Pacific | ▲ 2,325 | ▲ 7,900 |
| Vancouver - Main Long Room | British Columbia | Asia-Pacific | ▲ 2,227 | ▬ 60 |

**Table 26 Additional CPTPP Export Impact Top Ports of Clearance – Mean Results**

| POE | Province | Gateway | Tonnes | | $1000 [2015CAD] | |
|---|---|---|---|---|---|---|
| | | | Avg. | CV | Avg. | CV |
| Vancouver - Marine and Rail | British Columbia | Asia-Pacific | ▲ 754,624 | 0.15 | ▲ 1,068,819 | 0.03 |
| Vancouver - Int. Airport | British Columbia | Asia-Pacific | ▲ 64,640 | 0.56 | ▲ 141,580 | 0.48 |
| Calgary | Alberta | Asia-Pacific | ▲ 16,008 | 1.30 | ▲ 77,064 | 0.96 |
| Vancouver - Main Long Room | British Columbia | Asia-Pacific | ▲ 8,682 | 2.07 | ▲ 13,725 | 2.13 |
| Port Alberni | British Columbia | Asia-Pacific | ▲ 7,152 | 0.54 | ▲ 3,736 | 0.29 |
| Lethbridge | Alberta | Asia-Pacific | ▲ 6,707 | 0.59 | ▲ 2,479 | 0.37 |
| Nanaimo | British Columbia | Asia-Pacific | ▲ 5,890 | 1.48 | ▲ 5,182 | 0.56 |
| Montréal - Trudeau Int. Airport | Quebec | Continental | ▲ 4,792 | 0.31 | ▲ 42,859 | 0.46 |
| Niagara Falls | Ontario | Continental | ▲ 4,343 | 0.26 | ▲ 29,777 | 0.28 |
| Edmonton | Alberta | Asia-Pacific | ▲ 3,164 | 2.11 | ▲ 30,819 | 2.05 |

Figure 25 shows all the ports that ranked in the top ten for all simulated results and the fraction of the total observations that they placed in a certain rank. A total of 17 unique ports were ranked in the top ten over the 24 runs. The same procedure as before was used to create the other category. The 11 ports that are distinctly presented in the figure make up about 89% of all observations. The ports aggregated in the other category are Toronto -Main Long Room, Edmonton, Halifax, Montreal – Mirabel Int. Airport, Montreal – Main Long Room, and Lacolle.

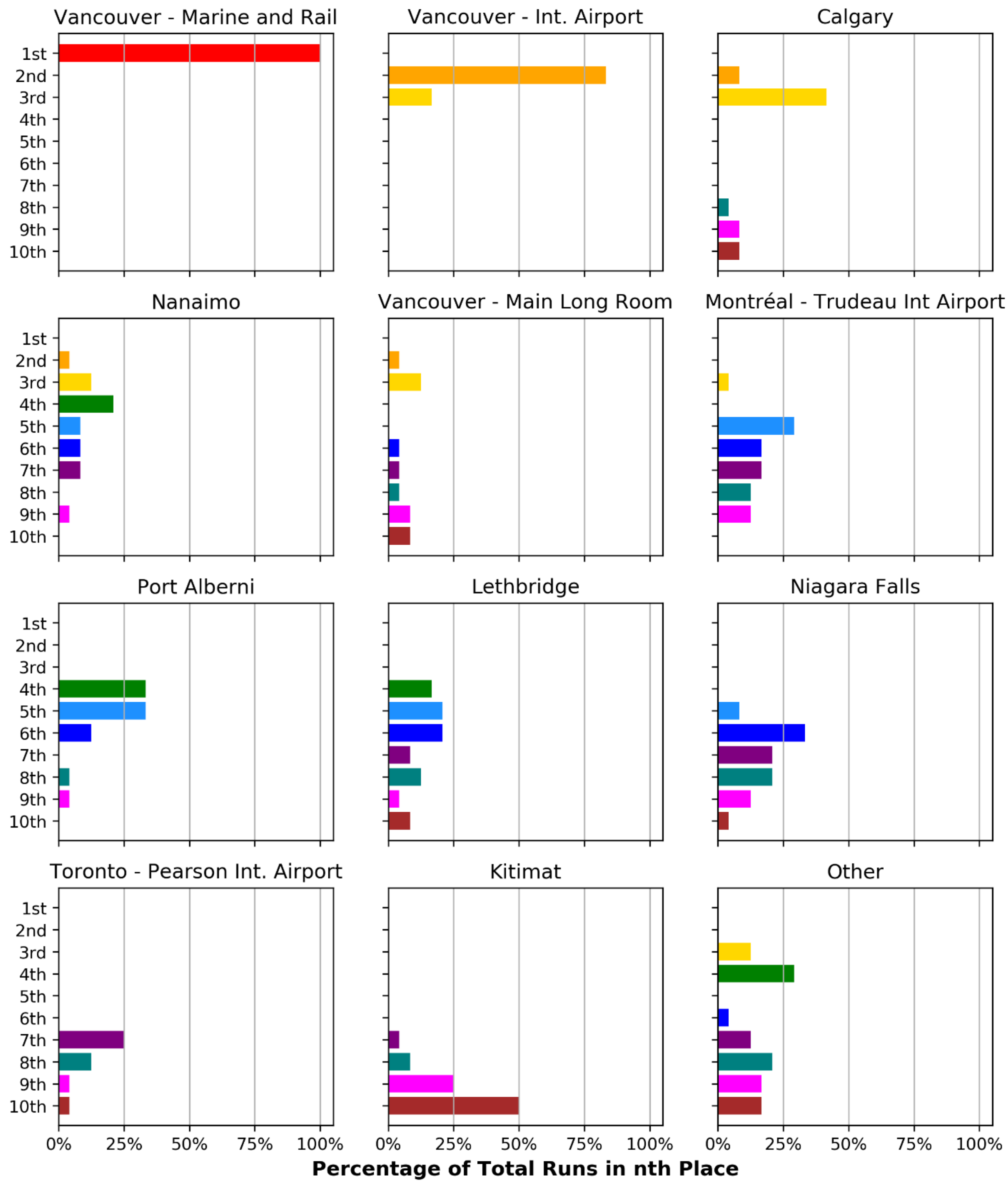


**Figure 25 Additional CPTPP Export Impact Top Ports of Clearance – All Ports in Top Ten**

Upon a visual inspection there appears to be more variation in this set of results than the previous one. All the ranked placements had at least 4 ports occupying them for a percentage of the runs. The only exception was the first place which was occupied by the Vancouver – Marine and Rail port for 100% of the runs.

The calculated $RRE_{wa}$ for the additional export impact results is 36.5% (see Table 27). Seven of the top ten ports of clearance are expected to be different between simulation runs ($RRE_{10}$ = 70%).

**Table 27 Rank Error Results for Additional CPTPP Export Impact Top Ports of Clearance**

| ***n*** | ***m*** | ***RREn*** |
|---|---|---|
| 1 | 1 | 0.00 |
| 2 | 1 | 0.50 |
| 3 | 2 | 0.33 |
| 4 | 2 | 0.50 |
| 5 | 2 | 0.60 |
| 6 | 2 | 0.67 |
| 7 | 2 | 0.71 |
| 8 | 2 | 0.75 |
| 9 | 2 | 0.78 |
| 10 | 3 | 0.70 |
| | ***RREwa*** | **36.51** |

Despite the slight increase in dispersion and moderately high $RRE_{wa}$, the major conclusion observed in the base case was also observed in the mean results of the repeated simulation. As expected, most the impacts of the CPTPP on exports are felt in ports of clearance that serve the Asia-Pacific and Continental gateways. This conclusion seems reasonable since these ports serve CPTPP countries.

The results of the analyses performed on the repeated simulation outputs for both the forecasted export growth and the additional export impacts of the CPTPP are promising for the port of clearance aggregations. Major conclusions are consistent with the base case for the aggregated top ten ports of clearance outcomes, despite the mean COVs of the first two sub-models in the disaggregated results indicating high variance (see these results in Section 4.1). The $RRE_{wa}$ values also suggest that using a single base case scenario may result in very different top ten port of clearance rankings depending on the base case selected. Lastly, there was higher dispersion on the results of the additional CPTPP export impacts; this was also observed in the gateway summary results.

#### 4.2.3. Domestic Summaries

The preliminary study presented separate summaries for the domestic freight flows between provinces by rail and truck. Two tables were created for each mode. The first table contained the domestic summary results for the forecasted export growth measured in yearly tonnes from 2015 to 2035 and the second table showed the results for the additional export impacts generated by the implementation of the CPTPP.

The repeated simulations generated 168 (6 x 4 x 7) tables of results for each mode and forecasted scenario (no CPTPP and implemented CPTPP). The domestic summaries were affected by the variation introduced in all the sub-models as they are created using the results of the output of the third sub-model ($t_{j,k,d}$). The same analyses described in Section 4.2 were applied to the domestic summary results.

#### 4.2.3.1. Domestic Movements by Rail

Descriptive statistics were calculated for the results of the repeated simulations regarding export trade growth between 2015-2035. Table 28 shows the means and Table 29 shows the COVs of the 168 tables created. As in the gateway summary analysis, the red colours represent COVs values indicating high variance (COV>1) and the yellow to green colours indicate low variance (COV<1). Finally, Table 30 shows the results of the CI analysis.

The COVs for the domestic summary of the rail mode can be seen in Table 29. There are values that are quite large in comparison to most other values. COV values over 5 were calculated for various exports (absolute values) from Prince Edward Island to other provinces. However, the movements mentioned in the major findings exhibit very low variance. If these types of results are used only for major findings, it seems that the variation is not affecting the domestic movements that have significantly large forecasted export growth from 2015 to 2035 with a few exceptions (e.g., exports from Quebec to itself and Alberta). Another notable result is the consistently low variance of the results for both absolute and relative export growth of movements to Ontario from other provinces. This means that after the three sources of variation are introduced, the movements of freight to Ontario for export are consistent.

CIs were constructed for all values. Then, the base case values were compared to the ranges of the CIs. Table 30 shows the results of the CI analysis directly on the base case values. Essentially, the table depicts the domestic summary for the rail mode obtained in the base study with colour coding illustrating the values that are within the 95% CIs. Green indicates that the CI analysis did not yield sufficient statistical evidence at the 95% confidence level to show that the base case value was not within the expected range of the mean; red indicates the opposite. A grey colour is added indicating the values that contained all zeros. If the mean of the output is zero, then the COV is not a number, as the mean is in the denominator of the COV formula (see Equation 12). The fractions of outputs that were within the CIs were calculated for the 99% 95%, and 90% confidence levels. The results were 48.6%, 31.4% and 25.7% for the absolute growth outputs (in yearly tonnage) and 49.2%, 40.0%, and 35.4% for the relative growth outputs (in percentage) for 99% 95%, and 90% confidence levels, respectively. The percentages are low, but they are higher than the results for the gateway summaries.

The results of the CI analysis yielded mostly low percentages. The percentages resulting from the comparison of the base case to the repeated simulation outputs were close to 50% for both the absolute and relative forecasted export growth outputs at the 99% level of confidence. However, they were low for the other two confidence levels. These results are in line with the trends observed in the gateway summaries. The base case seems to yield values that are more extreme than the central tendencies of the repeated simulation observations. It is also interesting to note that the base case absolute results for the movements to British Columbia from six of the provinces were within their respective CIs.

## Table 28 Mean Values for Forecasted Export Tonnage Growth – Domestic Summary (Rail)

| | | Province of Export | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **British Columbia** | **Alberta** | **Saskatchewan** | **Manitoba** | **Ontario** | **Quebec** | **New Brunswick** | **Nova Scotia** | **Newfoundland and Labrador** | **Prince Edward Island** |
| **[tonnes]** | | | | | | | | | | | |
| **Province of Origin** | **British Columbia** | 14,987,924 | 3,594 | 73,854 | 14,876 | 252,324 | 101,477 | 1,775 | 3,498 | 0 | 0 |
| | **Alberta** | 5,834,020 | 42,843 | 205,396 | 235,332 | 750,073 | 515,660 | 1,123 | 15,024 | 0 | 0 |
| | **Saskatchewan** | 9,690,422 | 27,939 | 4,591 | 261,446 | 724,044 | 824,172 | 5,458 | 49,294 | 0 | 0 |
| | **Manitoba** | 1,276,708 | 1,926 | 814 | 5,680 | 108,160 | 405,884 | 761 | 16,905 | 0 | 0 |
| | **Ontario** | 912,445 | 12,135 | 2,913 | 30,889 | 307,086 | 1,924,006 | 12,522 | 94,545 | 0 | 0 |
| | **Quebec** | 317,161 | 1,974 | 1,424 | 3,276 | 351,845 | 1,571,573 | 6,671 | 65,189 | 130 | 0 |
| | **New Brunswick** | 2,713 | 12 | 17 | 563 | 18,704 | 17,954 | 984,935 | 12,344 | 0 | 0 |
| | **Nova Scotia** | 718 | 34 | 2 | 26 | 23,509 | 6,242 | 602,810 | 5,879,045 | 0 | 0 |
| | **Newfoundland and Labrador** | 0 | 0 | 0 | 0 | 0 | 21,427,190 | 0 | 0 | 17 | 0 |
| | **Prince Edward Island** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Percentage [%]** | | | | | | | | | | | |
| **Province of Origin** | **British Columbia** | 41 | 7 | 4 | 8 | 10 | 22 | 13 | 60 | | |
| | **Alberta** | 32 | 6 | 16 | 6 | 6 | 22 | 5 | 24 | | |
| | **Saskatchewan** | 47 | 3 | 14 | 18 | 15 | 26 | 28 | 36 | | |
| | **Manitoba** | 43 | 6 | 9 | 12 | 15 | 36 | 14 | 36 | | |
| | **Ontario** | 49 | 18 | 11 | 18 | 15 | 41 | 23 | 37 | | |
| | **Quebec** | 53 | 24 | 9 | 8 | 17 | 53 | 12 | 51 | 62 | |
| | **New Brunswick** | 39 | 10 | 13 | 10 | 7 | 14 | 50 | 65 | | |
| | **Nova Scotia** | 42 | 18 | | 16 | 17 | 11 | 14 | 18 | | |
| | **Newfoundland and Labrador** | | | | | | 83 | | | | |
| | **Prince Edward Island** | | | | | | | | | | |

**Table 29 COVs for Forecasted Export Tonnage Growth - Domestic Summary (Rail)**

| | | Province of Export | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | British Columbia | Alberta | Saskatchewan | Manitoba | Ontario | Quebec | New Brunswick | Nova Scotia | Newfoundland and Labrador | Prince Edward Island |
| **Coefficient of Variation for Absolute Growth [-]** | | | | | | | | | | | |
| Province of Origin | **British Columbia** | 0.088 | 0.431 | 0.359 | 0.468 | 0.220 | 0.216 | 0.506 | 0.461 | | 7.223 |
| | **Alberta** | 0.111 | 0.829 | 0.241 | 0.457 | 0.117 | 0.831 | 0.791 | 0.670 | | |
| | **Saskatchewan** | 0.088 | 0.487 | 0.527 | 0.226 | 0.086 | 0.137 | 1.367 | 0.493 | | |
| | **Manitoba** | 0.531 | 0.615 | 0.695 | 0.386 | 0.283 | 0.915 | 0.705 | 0.875 | | |
| | **Ontario** | 0.384 | 0.686 | 0.284 | 0.231 | 0.291 | 1.409 | 0.641 | 0.315 | | 6.454 |
| | **Quebec** | 0.262 | 1.634 | 0.763 | 0.350 | 0.097 | 1.072 | 0.793 | 0.331 | 1.585 | 5.078 |
| | **New Brunswick** | 0.713 | 0.626 | 0.766 | 1.259 | 0.188 | 0.716 | 1.624 | 1.127 | | |
| | **Nova Scotia** | 1.248 | 0.941 | 0.942 | 0.964 | 0.281 | 0.453 | 2.033 | 0.820 | | |
| | **Newfoundland and Labrador** | | | | | | 0.369 | | | 2.667 | |
| | **Prince Edward Island** | | | | | | | | | | |
| **Coefficient of Variation for Relative Growth [-]** | | | | | | | | | | | |
| Province of Origin | **British Columbia** | 0.129 | 0.250 | 0.240 | 0.123 | 0.136 | 0.099 | 0.624 | 0.103 | | |
| | **Alberta** | 0.166 | 0.683 | 0.256 | 0.421 | 0.103 | 0.598 | 0.475 | 0.573 | | |
| | **Saskatchewan** | 0.050 | 0.117 | 0.332 | 0.087 | 0.082 | 0.090 | 0.705 | 0.262 | | |
| | **Manitoba** | 0.362 | 1.008 | 0.341 | 0.172 | 0.259 | 0.241 | 0.338 | 0.239 | | |
| | **Ontario** | 0.122 | 0.644 | 0.167 | 0.088 | 0.152 | 0.510 | 0.430 | 0.200 | | |
| | **Quebec** | 0.158 | 0.699 | 0.101 | 0.198 | 0.089 | 0.186 | 0.418 | 0.316 | 0.583 | |
| | **New Brunswick** | 0.254 | 0.448 | 0.338 | 0.405 | 0.195 | 0.542 | 0.296 | 0.344 | | |
| | **Nova Scotia** | 0.565 | 0.291 | | 0.331 | 0.131 | 0.124 | 1.339 | 0.370 | | |
| | **Newfoundland and Labrador** | | | | | | 0.134 | | | | |
| | **Prince Edward Island** | | | | | | | | | | |

**Table 30 Base Case Values for Forecasted Export Tonnage Growth - Domestic Summary (Rail)**

| | | Province of Export | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | British Columbia | Alberta | Saskatchewan | Manitoba | Ontario | Quebec | New Brunswick | Nova Scotia | Newfoundland and Labrador | Prince Edward Island |
| **Tonnes** | | | | | | | | | | | |
| Province of Origin | British Columbia | 16,382,114 | 2,491 | 55,290 | 11,168 | 246,276 | 103,708 | 2,647 | 1,746 | 0 | 0 |
| | Alberta | 4,878,928 | 139,441 | 166,265 | 138,152 | 828,940 | 389,924 | 1,239 | 5,121 | 0 | 0 |
| | Saskatchewan | 11,077,173 | 38,680 | 2,612 | 209,499 | 737,516 | 881,017 | 9,426 | 32,041 | 0 | 0 |
| | Manitoba | 1,014,174 | 1,341 | 552 | 3,957 | 89,614 | 252,994 | 521 | 1,776 | 0 | 0 |
| | Ontario | 981,845 | 4,476 | 2,480 | 24,914 | 247,105 | 8,913,317 | 11,719 | 109,604 | 0 | 0 |
| | Quebec | 314,792 | 1,054 | 2,648 | 3,909 | 351,071 | 5,491,679 | 2,739 | 68,113 | 40 | 0 |
| | New Brunswick | 3,463 | 13 | 11 | 210 | 21,821 | 18,815 | 622,816 | 389 | 0 | 0 |
| | Nova Scotia | 492 | 54 | 4 | 10 | 15,946 | 3,116 | 4,735,206 | 17,572,602 | 0 | 0 |
| | Newfoundland and Labrador | 0 | 0 | 0 | 0 | 0 | 16,043,738 | 0 | 0 | 0 | 0 |
| | Prince Edward Island | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Percentage [%]** | | | | | | | | | | | |
| Province of Origin | British Columbia | 37 | 7 | 4 | 9 | 9 | 21 | 9 | 58 | | |
| | Alberta | 25 | 25 | 10 | 3 | 6 | 12 | 5 | 41 | | |
| | Saskatchewan | 51 | 3 | 15 | 18 | 14 | 24 | 19 | 42 | | |
| | Manitoba | 39 | 3 | 15 | 14 | 14 | 38 | 14 | 30 | | |
| | Ontario | 42 | 11 | 11 | 18 | 13 | 95 | 25 | 29 | | |
| | Quebec | 51 | 20 | 8 | 8 | 16 | 56 | 8 | 36 | 49 | |
| | New Brunswick | 57 | 10 | 10 | 10 | 8 | 9 | 66 | 63 | | |
| | Nova Scotia | 28 | 21 | 24 | 23 | 16 | 12 | 56 | 22 | | |
| | Newfoundland and Labrador | | | | | | 79 | | | 46 | |
| | Prince Edward Island | | | | | | | | | | |

Some major findings from the preliminary study can be concluded using the mean data and some are different. The preliminary study concluded that the largest impacts due to forecasted absolute growth were seen in exports carried by rail to British Columbia from itself and from Saskatchewan on the west coast. On the east coast, the largest increase in exports was seen in the movements from Nova Scotia to itself and movements from Newfoundland and Labrador to Quebec. In central Canada, exports due to absolute trade growth are largest for movements to Quebec from itself and Ontario. The mean values also showed the same conclusions. However, the mean forecasted export growth yearly tonnages are lower than the base case values for these domestic movements, except for the exports from Newfoundland and Labrador to Quebec which were higher. Lastly, the base case indicated that the highest forecasted relative growth was seen in movements from Ontario shipped via rail to Quebec, a 95% increase. However, this value was much lower in the mean outputs (41%) and was not the highest.

The analyses were repeated for the domestic summary of the additional export impacts caused by implementing the CPTPP from 2015-2035 for the domestic rail mode. The results are presented in Table 31, Table 32, and Table 33.

The dispersion of the results varies largely. A high number of COV values indicate low variance; although, these are higher than the dispersion values observed in the gateway summary analysis (see Table 20). However, there are two domestic movements that exhibit extreme values of dispersion. The COVs of the additional impacts on exports from British Columbia to Nova Scotia and Quebec to Newfoundland and Labrador via rail are 76.6 and 56.5, respectively. These values indicate extremely high variances. One explanation for this behavior lies in the signs of the results. The domestic trade flows presented can be negative, zero, or positive depending on the additional impact of the CPTPP on that movement (i.e., trade flows can decrease, stay the same, or increase after the CPTPP is introduced, when compared to the forecasted growth only scenario). In the case of those extreme dispersions, negative and positive values may be present, making the variation very large. Interestingly, the variance is small for the relative additional export growth seen in rail shipments to Ontario from most of the provinces (except shipments with relative additional export values averaging zero).

The CI analysis yielded similar percentages for the additional export results as the forecasted growth results. The results were 48.6%, 31.4% and 25.7% for the 99%, 95%, and 90% confidence levels, respectively. At the 95% confidence level, there was enough statistical evidence to prove that ~69% of the base case results are not within the expected range of the central tendency of the repeated simulation observations. This is lower than the result of the gateway summary analysis (~88%) although the domestic movements have an extra source of uncertainty (recall the domestic shares varied over 7 CFAF years of data).

## Table 31 Mean Values for Additional CPTPP Export Tonnage Impact – Domestic Summary (Rail)

| | | Province of Export | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | British Columbia | Alberta | Saskatchewan | Manitoba | Ontario | Quebec | New Brunswick | Nova Scotia | Newfoundland and Labrador | Prince Edward Island |
| | | [tonnes] | | | | | | | | | |
| Province of Origin | British Columbia | 30,978 | -57 | -1,652 | -393 | -6,760 | -1,280 | -48 | -1 | 0 | 0 |
| | Alberta | 124,309 | 308 | -1,779 | -3,072 | -11,664 | -6,746 | -39 | -166 | 0 | 0 |
| | Saskatchewan | 19,814 | -454 | -79 | -3,561 | -17,285 | -33,041 | -60 | -2,261 | 0 | 0 |
| | Manitoba | 14,079 | -26 | -30 | -135 | -3,153 | -7,402 | -20 | -480 | 0 | 0 |
| | Ontario | 246,321 | -176 | -75 | -467 | -3,055 | -8,558 | -129 | -58 | 0 | 0 |
| | Quebec | 14,996 | -11 | -49 | -94 | -5,222 | -2,606 | -77 | 219 | 0 | 0 |
| | New Brunswick | 217 | 0 | 0 | -12 | -497 | -251 | -2,482 | -58 | 0 | 0 |
| | Nova Scotia | -1 | -1 | 0 | -1 | -329 | -120 | -3,111 | -31,500 | 0 | 0 |
| | Newfoundland and Labrador | 0 | 0 | 0 | 0 | 0 | -30,243 | 0 | 0 | 0 | 0 |
| | Prince Edward Island | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

## Table 32 COVs for Additional CPTPP Export Tonnage Impact – Domestic Summary (Rail)

| | | Province of Export | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | British Columbia | Alberta | Saskatchewan | Manitoba | Ontario | Quebec | New Brunswick | Nova Scotia | Newfoundland and Labrador | Prince Edward Island |
| | | [-] | | | | | | | | | |
| Province of Origin | British Columbia | 0.306 | 0.494 | 0.334 | 0.532 | 0.190 | 0.191 | 0.540 | 73.580 | | 7.223 |
| | Alberta | 0.224 | 3.978 | 0.246 | 0.378 | 0.137 | 0.542 | 0.995 | 0.869 | | |
| | Saskatchewan | 0.984 | 0.499 | 0.593 | 0.357 | 0.144 | 0.153 | 0.695 | 0.438 | | |
| | Manitoba | 0.698 | 0.553 | 0.924 | 0.811 | 0.340 | 0.202 | 0.480 | 0.801 | | |
| | Ontario | 0.224 | 0.415 | 0.511 | 0.337 | 0.221 | 0.514 | 0.551 | 6.601 | | 6.454 |
| | Quebec | 0.234 | 2.777 | 0.672 | 0.727 | 0.100 | 1.357 | 0.261 | 1.720 | 56.517 | 4.826 |
| | New Brunswick | 1.734 | 4.360 | 0.843 | 1.306 | 0.187 | 0.602 | 1.233 | 1.133 | | |
| | Nova Scotia | 9.836 | 1.917 | 0.754 | 0.998 | 0.347 | 0.683 | 1.060 | 0.649 | | |
| | Newfoundland and Labrador | | | | | | 0.290 | | | 2.462 | |
| | Prince Edward Island | | | | | | | | | | |

**Table 33 Base Case Values for Additional CPTPP Export Tonnage Impact - Domestic Summary (Rail)**

| | | Province of Export | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | British Columbia | Alberta | Saskatchewan | Manitoba | Ontario | Quebec | New Brunswick | Nova Scotia | Newfoundland and Labrador | Prince Edward Island |
| | | [tonnes] | | | | | | | | | |
| Province of Origin | **British Columbia** | 35,961 | -42 | -1,225 | -296 | -7,302 | -1,484 | -78 | -3 | 0 | 0 |
| | **Alberta** | 142,483 | 3,970 | -1,553 | -2,008 | -13,485 | -9,529 | -116 | -28 | 0 | 0 |
| | **Saskatchewan** | -1,012 | -633 | -25 | -2,963 | -20,546 | -39,794 | -146 | -1,907 | 0 | 0 |
| | **Manitoba** | 7,355 | -21 | -8 | -23 | -2,433 | -6,021 | -16 | -81 | 0 | 0 |
| | **Ontario** | 285,847 | -107 | -50 | -406 | -2,433 | -14,221 | -110 | -119 | 0 | 0 |
| | **Quebec** | 12,663 | -13 | -92 | -147 | -5,858 | 17,466 | -58 | -146 | 0 | 0 |
| | **New Brunswick** | -10 | 3 | 0 | -6 | -662 | -416 | -1,476 | -1 | 0 | 0 |
| | **Nova Scotia** | 1 | 0 | 0 | 0 | -244 | -66 | -10,018 | -54,954 | 0 | 0 |
| | **Newfoundland and Labrador** | 0 | 0 | 0 | 0 | 0 | -24,953 | 0 | 0 | 0 | 0 |
| | **Prince Edward Island** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

The major conclusions were the same using the base case outputs and the mean outputs of the repeated simulations. In both scenarios, the largest additional impacts on exports were seen in the domestic movements to British Columbia from Ontario and from Alberta (smaller impact) via rail. The outputs from the base case were larger than those from the repeated simulation but they were close. It can also be concluded, using both set of results, that trade diversion occurred as freight shipped to Quebec and Ontario for export from almost all other provinces decreased. The reason for the agreement between the major conclusions of both sets of results was already explained in the disaggregated analysis. From the second to third sub-models, over 190 million supply chains were aggregated into 363 domestic movements. This large aggregation generates better results for the domestic movement summary even as a new source of uncertainty is introduced.

#### 4.2.3.2. Domestic Movements by Truck

Descriptive statistics were calculated for the 168 sets of results generated through repeated simulations for forecasted export trade growth between 2015-2035. Table 34 and Table 35 show the means the COVs calculated. Table 35 is colour coded as previously described with red indication high variance (COV>1), and yellow-green indicating low variance (COV<1), and grey indicating the values that contained all zeros.

The COVs for the truck movements were smaller than those of the rail movements (Table 29). Similar to the results for rail, the shipments to Ontario for export from all provinces exhibited low variance. The instances of high variance were mostly seen in the absolute export growth results of movements to and from the provinces of Newfoundland and Labrador and Prince Edward Island. This may be the result of lower traffic of commodities into those provinces as they are smaller in size. Once again, most movements exhibited low variance (COV<1) for both relative and absolute export growth results.

As before, CIs were constructed, and the base case values were compared to the ranges of the CIs. The results are presented in Table 36. On the table, green indicates that the CI analysis did not yield sufficient statistical evidence to show that the base case value was not within the expected range on average at the 95% confidence level. Red indicates the opposite and grey depicts the values for which the mean was zero. The ranges of the CIs were compared to the base case outputs. The resulting percentages refer to the fractions of outputs that were within the CIs for the 99% 95%, and 90% confidence levels. The results were 45.5%, 35.4% and 21.2% for the absolute growth outputs and 40.9%, 30.7%, and 22.7% for the relative growth outputs for 99% 95%, and 90% confidence levels, respectively. These percentages are very similar to the ones obtained for the domestic summary of the rail mode.

The results of the CI analysis are similar to the rail movements. They yielded mostly low percentages except for the results for the absolute growth values which were close to close to 50% at the 99% confidence level. The other percentages were low. The base case data seem to yield values that are outside of the expected central tendency results obtained from the total available data, a trend seen throughout this case study. Nevertheless, as in all the other aggregated results, this did not largely affect the conclusions of the major findings.

## Table 34 Mean Values for Forecasted Export Tonnage Growth – Domestic Summary (Truck)

| | | Province of Export | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | British Columbia | Alberta | Saskatchewan | Manitoba | Ontario | Quebec | New Brunswick | Nova Scotia | Newfoundland and Labrador | Prince Edward Island |
| [tonnes] | | | | | | | | | | | |
| Province of Origin | **British Columbia** | 20,791,806 | 9,001 | 58,134 | 10,724 | 67,350 | 19,151 | 322 | 2,446 | 48 | 0 |
| | **Alberta** | 1,365,962 | 1,718,177 | 458,559 | 79,785 | 115,092 | 161,893 | 137 | 10,854 | 396 | 0 |
| | **Saskatchewan** | 76,452 | 151,737 | 257,002 | 191,383 | 26,717 | 16,163 | 350 | 419 | 1 | 0 |
| | **Manitoba** | 305,527 | 7,090 | 8,979 | 347,226 | 82,134 | 54,925 | 381 | 9,754 | 18 | 36 |
| | **Ontario** | 574,353 | 9,611 | 3,671 | 25,349 | 7,277,898 | 3,635,603 | 46,214 | 128,425 | 251,863 | 17,116 |
| | **Quebec** | 98,356 | 1,972 | 643 | 1,306 | 1,340,419 | 24,453,180 | 27,917 | 163,767 | 2,444 | 19 |
| | **New Brunswick** | 2,015 | 14 | 20 | 1,060 | 34,415 | 80,618 | 5,838,139 | 367,072 | 1,430 | 441 |
| | **Nova Scotia** | 39,050 | 20 | 2 | 18 | 44,519 | 22,017 | 121,066 | 2,269,993 | 43,174 | 0 |
| | **Newfoundland and Labrador** | 6,309 | 15 | 1 | 1 | 1,746 | 12,582 | 5,825 | 277,730 | 24,959,881 | 0 |
| | **Prince Edward Island** | 536 | 1 | 1 | -4 | 5,840 | 4,825 | 14,356 | 18,872 | 379 | 8,597 |
| Percentage [%] | | | | | | | | | | | |
| Province of Origin | **British Columbia** | 34 | 6 | 9 | 9 | 9 | 24 | 14 | 59 | 41 | |
| | **Alberta** | 31 | 4 | 6 | 9 | 15 | 42 | 19 | 45 | 27 | |
| | **Saskatchewan** | 39 | 3 | 8 | 11 | 11 | 28 | 21 | 46 | | |
| | **Manitoba** | 68 | 5 | 7 | 10 | 23 | 50 | 19 | 86 | | |
| | **Ontario** | 56 | 22 | 10 | 16 | 12 | 41 | 32 | 38 | 34 | 37 |
| | **Quebec** | 45 | 29 | 8 | 8 | 16 | 57 | 15 | 45 | 16 | 48 |
| | **New Brunswick** | 33 | 12 | 12 | 10 | 9 | 14 | 29 | 61 | 12 | |
| | **Nova Scotia** | 33 | 13 | 23 | 12 | 17 | 12 | 14 | 24 | 26 | |
| | **Newfoundland and Labrador** | 50 | 23 | | | 12 | 21 | 9 | 30 | 49 | |
| | **Prince Edward Island** | 37 | 4 | | 3 | 23 | 29 | 9 | 30 | 44 | 25 |

**Table 35 COVs for Forecasted Export Tonnage Growth - Domestic Summary (Truck)**

| | | Province of Export | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | British Columbia | Alberta | Saskatchewan | Manitoba | Ontario | Quebec | New Brunswick | Nova Scotia | Newfoundland and Labrador | Prince Edward Island |
| **Coefficient of Variation for Absolute Growth[-]** | | | | | | | | | | | |
| Province of Origin | **British Columbia** | 0.206 | 0.308 | 0.297 | 0.524 | 0.308 | 0.285 | 0.654 | 0.798 | 1.958 | 1.400 |
| | **Alberta** | 0.184 | 0.249 | 0.276 | 0.286 | 0.313 | 1.626 | 0.686 | 0.466 | 1.051 | 1.438 |
| | **Saskatchewan** | 0.403 | 0.131 | 0.257 | 0.238 | 0.316 | 0.804 | 4.041 | 1.464 | 2.256 | 2.602 |
| | **Manitoba** | 1.047 | 0.270 | 0.189 | 0.112 | 0.317 | 0.446 | 0.801 | 0.847 | 1.195 | 2.450 |
| | **Ontario** | 0.634 | 0.962 | 0.375 | 0.254 | 0.091 | 1.164 | 0.840 | 0.506 | 2.678 | 2.585 |
| | **Quebec** | 0.303 | 1.891 | 0.987 | 0.430 | 0.102 | 0.232 | 0.430 | 0.335 | 0.767 | 1.606 |
| | **New Brunswick** | 0.933 | 0.422 | 0.800 | 1.195 | 0.162 | 0.664 | 1.076 | 0.429 | 0.454 | 0.823 |
| | **Nova Scotia** | 2.965 | 1.002 | 0.919 | 0.741 | 0.228 | 0.337 | 1.113 | 0.771 | 2.500 | 2.233 |
| | **Newfoundland and Labrador** | 3.382 | 2.281 | 2.240 | 2.267 | 0.277 | 1.344 | 0.469 | 0.680 | 1.009 | |
| | **Prince Edward Island** | 0.698 | 7.723 | 3.173 | 3.740 | 0.406 | 0.704 | 0.128 | 0.228 | 1.666 | 0.253 |
| **Coefficient of Variation for Relative Growth [-]** | | | | | | | | | | | |
| Province of Origin | **British Columbia** | 0.381 | 0.216 | 0.129 | 0.049 | 0.029 | 0.198 | 0.442 | 0.355 | 0.457 | |
| | **Alberta** | 0.209 | 0.207 | 0.278 | 0.248 | 0.131 | 0.634 | 0.556 | 0.209 | 0.946 | |
| | **Saskatchewan** | 0.211 | 0.052 | 0.141 | 0.145 | 0.309 | 0.097 | 0.639 | 0.227 | | |
| | **Manitoba** | 0.311 | 0.539 | 0.091 | 0.046 | 0.326 | 0.141 | 0.571 | 0.276 | | |
| | **Ontario** | 0.203 | 0.684 | 0.157 | 0.084 | 0.106 | 0.454 | 0.411 | 0.224 | 0.696 | 0.502 |
| | **Quebec** | 0.199 | 0.855 | 0.167 | 0.403 | 0.126 | 0.137 | 0.330 | 0.453 | 0.468 | 0.660 |
| | **New Brunswick** | 0.301 | 0.316 | 0.400 | 0.357 | 0.139 | 0.642 | 0.568 | 0.139 | 1.502 | |
| | **Nova Scotia** | 0.587 | 0.554 | 0.398 | 0.353 | 0.117 | 0.152 | 0.582 | 0.256 | 0.980 | |
| | **Newfoundland and Labrador** | 0.479 | 0.872 | | | 0.135 | 0.674 | 0.218 | 0.577 | 0.315 | |
| | **Prince Edward Island** | 0.397 | 2.414 | | 1.733 | 0.258 | 0.186 | 0.091 | 0.127 | 0.585 | 0.065 |

**Table 36 Base Case Values for Forecasted Export Tonnage Growth - Domestic Summary (Truck)**

| | | Province of Export | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **British Columbia** | **Alberta** | **Saskatchewan** | **Manitoba** | **Ontario** | **Quebec** | **New Brunswick** | **Nova Scotia** | **Newfoundland and Labrador** | **Prince Edward Island** |
| **[tonnes]** | | | | | | | | | | | |
| **Province of Origin** | **British Columbia** | 20,388,789 | 6,527 | 101,175 | 8,009 | 128,465 | 21,387 | 220 | 858 | 4 | 0 |
| | **Alberta** | 1,305,402 | 3,072,699 | 510,969 | 59,757 | 138,326 | 60,420 | 212 | 7,324 | 53 | 0 |
| | **Saskatchewan** | 139,518 | 133,076 | 283,229 | 275,880 | 27,385 | 13,649 | 27 | 34 | 1 | 0 |
| | **Manitoba** | 74,511 | 10,874 | 8,330 | 354,230 | 77,381 | 16,485 | 521 | 3,085 | 12 | 0 |
| | **Ontario** | 2,191,367 | 2,370 | 2,868 | 31,287 | 8,360,433 | 18,400,476 | 48,676 | 160,085 | 283 | 6 |
| | **Quebec** | 148,269 | 613 | 769 | 1,475 | 1,307,327 | 20,673,155 | 15,680 | 158,577 | 706 | 0 |
| | **New Brunswick** | 456 | 25 | 33 | 177 | 31,790 | 75,926 | 24,338,083 | 127,750 | 745 | 0 |
| | **Nova Scotia** | 538,371 | 27 | 1 | 6 | 38,116 | 15,096 | 289,929 | 3,088,346 | 37 | 0 |
| | **Newfoundland and Labrador** | 936 | 8 | 6 | 0 | 2,687 | 16,025 | 4,052 | 366,517 | 73,673,326 | 0 |
| | **Prince Edward Island** | 796 | -2 | 11 | 0 | 5,856 | 4,804 | 13,651 | 16,204 | 2 | 4,387 |
| **Percentage [%]** | | | | | | | | | | | |
| **Province of Origin** | **British Columbia** | 23 | 6 | 9 | 9 | 9 | 25 | 10 | 40 | 43 | 65 |
| | **Alberta** | 23 | 6 | 4 | 8 | 13 | 31 | 10 | 40 | 68 | 45 |
| | **Saskatchewan** | 35 | 3 | 9 | 13 | 11 | 27 | 21 | 37 | 53 | |
| | **Manitoba** | 37 | 3 | 8 | 10 | 20 | 43 | 15 | 62 | 50 | |
| | **Ontario** | 97 | 10 | 9 | 16 | 10 | 92 | 41 | 12 | 7 | 1 |
| | **Quebec** | 39 | 12 | 8 | 5 | 14 | 48 | 12 | 16 | 15 | 8 |
| | **New Brunswick** | 19 | 11 | 23 | 11 | 10 | 9 | 62 | 55 | 7 | |
| | **Nova Scotia** | 6 | 10 | 24 | 10 | 16 | 12 | 37 | 27 | 36 | |
| | **Newfoundland and Labrador** | 53 | 14 | 14 | | 9 | 18 | 9 | 54 | 64 | |
| | **Prince Edward Island** | 50 | -1 | 23 | -2 | 28 | 20 | 10 | 30 | 39 | 23 |

Like the rail results, some of the major findings of the base case are confirmed with the results of the mean outputs and some are not. Both sets of outputs demonstrated larger forecasted export growth on movements carried by truck than rail. Moreover, the largest forecasted absolute export growth in Western Canada was in exports produced in and transported via truck to British Columbia for export according to both results. In both cases, the largest absolute export growth in Eastern Canada was the exports produced in and shipped via truck to Newfoundland and Labrador. Although, the latter value was over 70 million tonnes in the base case, and it much lower in the mean results (over 20 million tonnes). For Central Canada, shipments from Ontario and Quebec to Quebec were found to have the largest forecasted growth in the base case. However, in the simulated results, shipments from Ontario to itself experienced larger export growth (over 7 million tonnes) on average than shipments from Ontario to Quebec (over 3 million tonnes). This is a reasonable deviation as the results for the movements from Ontario to Quebec exhibited high variance. On average, the highest relative export growth was seen in truck shipments from New Brunswick to Nova Scotia (61%), but in the base case this was seen in truck shipments from Ontario to British Columbia (97% in base case, 56% on average). Similarly, exports from Ontario to Quebec exhibited a large relative growth in the base case (92%) but it was not as extreme in the mean results (56%).

The additional export impacts of implementing the CPTPP from 2015-2035 on domestic truck movements were analyzed using the same procedure. The results are presented in Table 37, Table 38, and Table 39.

As in the forecasted growth results, the dispersion values generally indicated low variance except for most shipments within the eastern provinces (see Table 37). However, the dispersion values are higher overall than the ones observed in the forecasted growth results. Interestingly, the additional export impact for shipments from Newfoundland to Ontario had the highest coefficient of variation (~37); the trend in all the previous domestic summary results was that all COVs for the movements to Ontario from most of the provinces exhibited low variance (see Table 29, Table 32, and Table 35).

The CI analysis yielded slightly higher percentages for the additional impact results than the forecasted export growth results. The results were 49.5%, 38.4% and 27.3% for the 99%, 95%, and 90% confidence levels, respectively. These values confirm the trend seen throughout the analysis of the aggregated results. The base case data seem to yield values that are more extreme than the central tendency of the simulated outputs.

The major finding of the base case is confirmed using the mean outputs for the additional impacts on exports of the CPTPP. Both results see an increase in shipments to British Columbia from itself and Alberta. However, the magnitudes are switched with the impacts to shipments from Alberta being lower than those from British Columbia on average. In both cases, the trend of trade dispersion is seen in shipments to Ontario and Quebec, a behaviour also seen in the rail shipments.

**Table 37 Mean Values for Additional CPTPP Export Tonnage Impact – Domestic Summary (Truck)**

| Province of Origin | Province of Export: British Columbia | Alberta | Saskatchewan | Manitoba | Ontario | Quebec | New Brunswick | Nova Scotia | Newfoundland and Labrador | Prince Edward Island |
|---|---|---|---|---|---|---|---|---|---|---|
| | [tonnes] | | | | | | | | | |
| British Columbia | 122,918 | -117 | -1,619 | -305 | -2,023 | -209 | -6 | -7 | -1 | 0 |
| Alberta | 99,908 | -4,830 | -6,960 | -2,424 | -2,105 | -865 | -3 | -88 | -6 | 0 |
| Saskatchewan | 2,065 | -3,016 | -8,010 | -5,437 | -578 | -589 | -3 | -2 | 0 | 0 |
| Manitoba | 11,386 | -202 | -491 | -11,341 | -806 | -505 | -7 | -23 | 0 | -3 |
| Ontario | 66,035 | -124 | -135 | -529 | -101,692 | -12,921 | -426 | 55 | -427 | -106 |
| Quebec | 13,490 | -16 | -27 | -49 | -22,531 | -59,466 | -535 | 666 | -60 | 0 |
| New Brunswick | 267 | 0 | 0 | -22 | -806 | -1,422 | -17,985 | 2,827 | -7 | -32 |
| Nova Scotia | -603 | 0 | 0 | -1 | -624 | -333 | -1,516 | -9,721 | -100 | 0 |
| Newfoundland and Labrador | -81 | 1 | 0 | 0 | 1 | -115 | -122 | 60 | -51,802 | 0 |
| Prince Edward Island | 21 | -3 | 0 | -4 | -87 | -57 | -1,172 | 749 | -3 | -693 |

**Table 38 COVs for Additional CPTPP Export Tonnage Impact – Domestic Summary (Truck)**

| | | Province of Export | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | British Columbia | Alberta | Saskatchewan | Manitoba | Ontario | Quebec | New Brunswick | Nova Scotia | Newfoundland and Labrador | Prince Edward Island |
| | | [-] | | | | | | | | | |
| Province of Origin | British Columbia | 0.256 | 0.960 | 0.289 | 0.547 | 0.314 | 0.390 | 0.641 | 2.864 | 2.478 | 2.883 |
| | Alberta | 0.205 | 3.478 | 0.282 | 0.303 | 0.337 | 1.051 | 0.953 | 0.794 | 1.174 | 1.539 |
| | Saskatchewan | 0.424 | 0.178 | 0.127 | 0.308 | 0.343 | 0.909 | 2.004 | 1.424 | 4.243 | 2.602 |
| | Manitoba | 0.261 | 0.348 | 0.153 | 0.126 | 0.201 | 0.450 | 0.709 | 1.153 | 1.566 | 2.450 |
| | Ontario | 0.412 | 0.505 | 0.459 | 0.270 | 0.115 | 0.485 | 0.879 | 10.306 | 2.720 | 2.614 |
| | Quebec | 0.289 | 1.475 | 0.698 | 1.232 | 0.060 | 0.628 | 0.242 | 1.470 | 0.906 | 1.539 |
| | New Brunswick | 1.555 | 5.463 | 0.791 | 1.210 | 0.140 | 0.236 | 0.620 | 0.582 | 3.230 | 0.827 |
| | Nova Scotia | 3.060 | 3.764 | 0.683 | 0.736 | 0.278 | 0.832 | 0.316 | 0.917 | 1.799 | 2.141 |
| | Newfoundland and Labrador | 4.162 | 2.334 | 2.240 | 2.417 | 37.360 | 1.036 | 0.355 | 29.422 | 0.931 | |
| | Prince Edward Island | 1.033 | 0.891 | 1.670 | 2.180 | 0.505 | 1.088 | 0.214 | 0.514 | 1.911 | 0.229 |

## Table 39 Base Case Values for Additional CPTPP Export Tonnage Impact – Domestic Summary (Truck)

| Province of Origin [tonnes] | British Columbia | Alberta | Saskatchewan | Manitoba | Ontario | Quebec | New Brunswick | Nova Scotia | Newfoundland and Labrador | Prince Edward Island |
|---|---|---|---|---|---|---|---|---|---|---|
| British Columbia | 112,614 | -146 | -2,665 | -271 | -3,962 | -241 | -6 | -2 | 0 | 0 |
| Alberta | 119,397 | 43,455 | -8,294 | -2,651 | -2,946 | -1,231 | -11 | -77 | 0 | 0 |
| Saskatchewan | 2,774 | -3,318 | -8,998 | -9,261 | -583 | -577 | 0 | 1 | 0 | 0 |
| Manitoba | 12,960 | -319 | -433 | -11,914 | -825 | -152 | -15 | -9 | 0 | 0 |
| Ontario | 42,467 | -81 | -134 | -706 | -105,374 | -32,294 | -433 | -1,436 | -7 | 5 |
| Quebec | 11,597 | -15 | -30 | -88 | -24,311 | 25,334 | -421 | -520 | -13 | 0 |
| New Brunswick | 29 | 6 | 0 | -4 | -729 | -1,694 | -49,789 | 3,968 | -7 | 0 |
| Nova Scotia | -8,550 | 0 | 0 | 0 | -538 | -251 | -1,510 | -12,548 | 0 | 0 |
| Newfoundland and Labrador | -2 | 0 | 0 | 0 | -55 | -260 | -105 | -395 | -150,537 | 0 |
| Prince Edward Island | -9 | -4 | 0 | 0 | -80 | -155 | -902 | 721 | 0 | -391 |

Columns: Province of Export

Overall, there are contradictions between the base case and the simulation results on some of the major findings for the domestic summaries. This occurs more often in these results than in the gate summary results. This is an expected observation as the domestic summaries include uncertainty from all three sources (supply chain shares, sector code aggregations, and domestic shares) whereas the gate summaries only include the uncertainty of the first two sources. However, there are still major conclusions that are consistent with the base case and the dispersion indicates low variance in general. This was also expected as the domestic results are highly aggregated.

### 4.3. Targeted Analyses

The targeted analyses were conducted to explore two aspects of this research. The first is to formally explore the assumption of normality throughout the sub-models and present a detailed statistical analysis for a single supply chain in the freight model. The second is to compare the uncertainty of analyzing a regular trade growth forecast versus analyzing the impacts of an FTA on trade (exports) using the same freight models. The US was selected for the analysis of export growth alone since it is Canada's largest trade partner, and thus consistent forecast results for this trade partner are important. For the FTA analysis, forecasted exports for the CPTPP signatories were aggregated so that it includes the countries of Australia, Chile, Japan, Malaysia, Mexico, Peru, New Zealand, Singapore, and Vietnam. Brunei was not included because it was not uniquely identified in the regions of the CGE economic model forecasts.

The procedure for the targeted analysis is the same as the one for the disaggregated outputs with the addition of graphical normality assumption tests. After the freight model is put through the repeated simulations described in Section 3.3.3, the first step is to calculate descriptive statistics for the outputs of each sub-model. The second step is to check the normality assumptions needed to use the student t-test statistic. The last step is to construct confidence intervals (CIs) for base case comparisons.

#### 4.3.1. US Results

Canada and the US have the largest trading partnership in the world (Government of Canada, 2021). One of the major trading sectors between the countries is the automobile industry. The CGE forecast uniquely identified automotive as one of its industries. Thus, the targeted analysis considered the automotive sector as the commodity of interest ($i$).

The rest of the supply chain, meaning subnational region of origin ($j$), subnational region of destination ($k$), international mode of transport ($m$), port of clearance ($n$), and domestic mode of transportation ($d$), were chosen based on the forecasted CGE results by selecting the highest forecasted yearly tonnage in 2035 (along with a check performed using the raw CSBA export data). The identified supply chain was: automobile exports ($i$), produced in Ontario (j), exported from Ontario ($k$) to the US ($l$) via international road mode ($m$), through the Windsor Ambassador Bridge ($n$). The domestic mode of transport was rail ($d$).

Descriptive statistics were used to create Figure 26. The COVs did not vary greatly between forecasts (i.e., between the CGE results for 2015, 2035, and 2035 after the CPTPP) thus the figure shows an example of the results using the CGE forecasts for 2035 – the similarity of COVs for the three export forecasts was observed and explained in the disaggregated results (see Section 4.1).

Figure 26 shows that the dispersion increases from the first to the second sub-model and then decreases by the third sub-model. The dispersion values indicate very low variance (COV<1) for all the sub-model outputs. This behaviour is opposite to the one observed when averaging the disaggregated outputs for all supply chains (see Figure 17), where the outputs of all sub-models exhibited high variance with the third being closer to 1. This means that the freight model with added uncertainty generates better results (less dispersion) for all the sub-model outputs of this supply chain than the results it generates on *average*. Unlike in the averaged disaggregated outputs, the dispersion of the third sub-model outputs is not lower than the dispersion of the first sub-model outputs. Moreover, the uncertainty introduced by varying the HS aggregation schemes in the second sub-model seem to have more effect on this supply chain (i.e., steeper slope between first and second sub-model results) than on average without raising the dispersion to high variance. The smaller dispersion can be explained by the fact that the US is a major trading partner. There are over 190 million different supply chains for the first two sub-models. Several of these supply chains are not highly utilized, meaning that there are multiple zeros. Any exports growth is more evident from year to year on these less utilized supply chains. However, exports to the US are more consistently large over the years because it is Canada's major trading partner, hence the lower dispersion for the targeted results when compared to the dispersion on average.

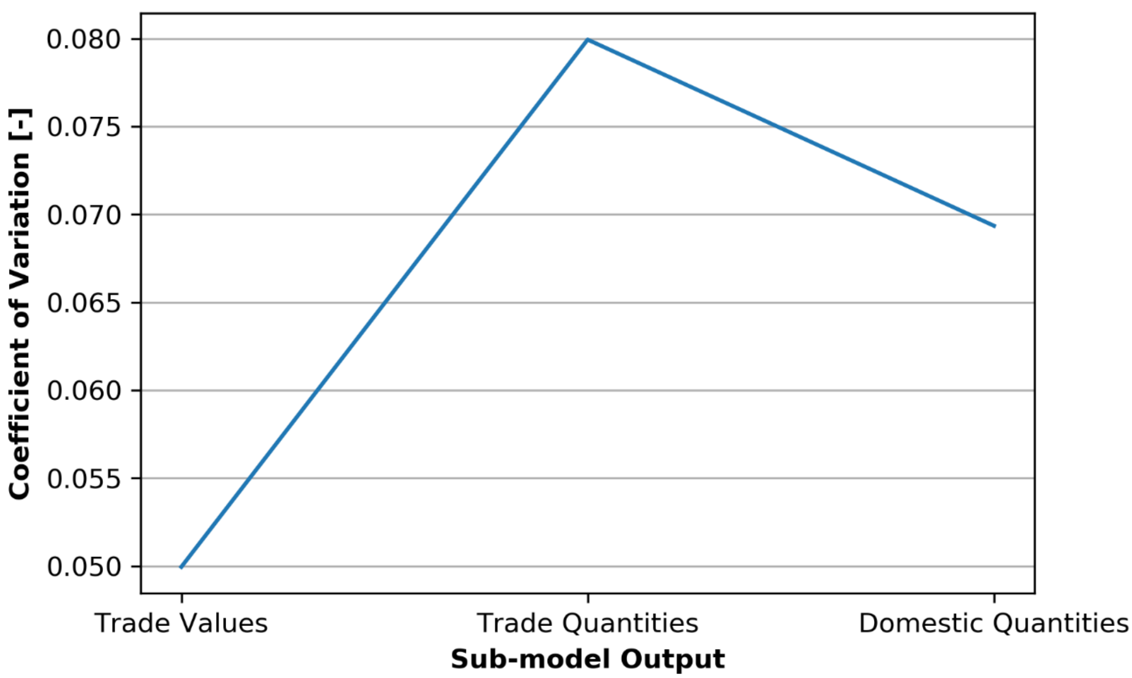


**Figure 26 US Targeted Analysis COVs for Each Sub-model (2035 CGE Forecast)**

The assumption of normality was checked before creating the confidence intervals. This was done graphically using normal probability plots and using the Shapiro-Wilk (SW) test. As previously mentioned, the sample means of the population being analyzed need to be normally distributed to use the t-factor as the multiplier to create confidence intervals. It is helpful that for large enough sample sizes the central limit theorem (CLT) can be used to prove that, on repeated random sampling of a population, the sample means are normally distribution. However, the less normal the original population is, the higher the sample size needs to be for the CLT to apply. Typically, a sample of size of 30 is used as the minimum. However, this number was empirically determined using the extreme case of exponentially distributed data. For data that are closer to normality, the sample size can be smaller for the CLT to apply.

In this study, it was determined that the outputs of the second and third sub-models met the criteria for the CLT to apply but the outputs of the first did not. The assumption had to be checked for the outputs of the first sub-model because if the sample observations are normally distributed then its sample means are as well. The outputs of the first sub-model were checked for normality using NPPs and the SW test to see if the results of the graphical method matched the results of the statistical test.

Figure 27 shows the NPP for the trade values (outputs of the first sub-model) for all the CGE forecasts. The results for this supply chain seem normally distributed because the values on the NPP generally follow a straight line for all forecasts.

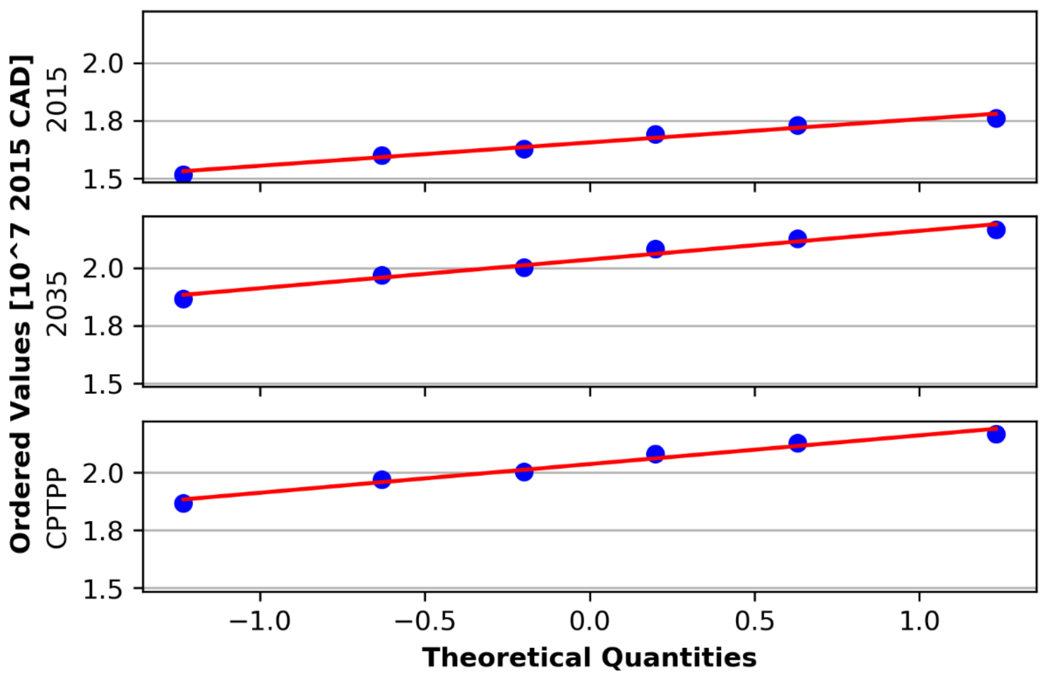


**Figure 27 NPP for the Outputs of First Sub-Model (US)**

The set up of the SW test is presented below:

$H_0$: sample is normally distributed

$H_1$: sample is not normally distributed

$\alpha$ : 0.05 (significance level)

Using Python, the W-value was calculated and compared to the critical value. The p-value of the results was 0.866. The p-value is higher than the significance level. This means that the test fails to reject the $H_0$ and the distribution output of the first sub-model for this supply chain is normally distributed. There is not enough statistical evidence to reject the $H_0$ even at a significance level of 0.1. These results are in accordance with the graphical results. Thus, it is safe to conclude that the sample mean is also normally distributed, and CIs can be constructed.

All the calculated results are tabulated in Table 40 for the output of the first sub-model ($z_{automobile,Ontario,Ontario,US,road,Windsor\ Ambassador\ Bridge}$) in yearly 2015 Canadian dollars, in Table 41 for the output of the second sub-model ($t_{automobile,Ontario,Ontario,US,road,Windsor\ Ambassador\ Bridge}$), and Table 42 for the output of the third sub-model ($t_{Ontario,Ontario,rail}$), both in yearly tonnes. Note that the tables include the results of the analysis for this supply chain using the CGE forecasts that include the CPTPP impacts in 2035 labelled simply as CPTPP.

**Table 40 Results of the First Sub-Model for a Single Supply Chain (US)**

| Forecast Year | | 2015 | 2035 | CPTPP |
|---|---|---|---|---|
| **Base** | | 15,173,423 | 20,813,894 | 18,676,944 |
| **Average** | | 16,550,278 | 20,356,845 | 20,371,714 |
| **COV** | | 0.050 | 0.050 | 0.050 |
| **90% CI** | **Upper** | 17,230,441 | 21,193,445 | 21,208,925 |
| | **Lower** | 15,870,115 | 19,520,245 | 19,534,502 |
| **95% CI** | **Upper** | 17,417,956 | 21,424,089 | 21,439,738 |
| | **Lower** | 15,682,600 | 19,289,600 | 19,303,689 |
| **99% CI** | **Upper** | 17,911,294 | 22,030,895 | 22,046,986 |
| | **Lower** | 15,189,262 | 18,682,795 | 18,696,441 |

**Table 41 Results of the Second Sub-Model for a Single Supply Chain (US)**

| Forecast Year | | 2015 | 2035 | CPTPP |
|---|---|---|---|---|
| **Base** | | 1,053,507 | 1,295,813 | 1,296,760 |
| **Average** | | 973,534 | 1,197,447 | 1,198,322 |
| **COV** | | 0.080 | 0.080 | 0.080 |
| **90% CI** | **Upper** | 1,000,761 | 1,230,936 | 1,231,835 |
| | **Lower** | 946,307 | 1,163,958 | 1,164,808 |
| **95% CI** | **Upper** | 1,006,397 | 1,237,869 | 1,238,773 |
| | **Lower** | 940,671 | 1,157,025 | 1,157,870 |
| **99% CI** | **Upper** | 1,018,132 | 1,252,302 | 1,253,217 |
| | **Lower** | 928,936 | 1,142,591 | 1,143,426 |

**Table 42 Results of the Third Sub-Model for a Single Supply Chain (US)**

| Forecast Year | | 2015 | 2035 | CPTPP |
|---|---|---|---|---|
| **Base** | | 1,309,386 | 1,610,545 | 1,611,721 |
| **Average** | | 1,338,626 | 1,646,510 | 1,647,713 |
| **COV** | | 0.069 | 0.069 | 0.069 |
| **90% CI** | **Upper** | 1,350,473 | 1,661,083 | 1,662,296 |
| | **Lower** | 1,326,778 | 1,631,938 | 1,633,130 |
| **95% CI** | **Upper** | 1,352,767 | 1,663,904 | 1,665,119 |
| | **Lower** | 1,324,485 | 1,629,116 | 1,630,306 |
| **99% CI** | **Upper** | 1,357,289 | 1,669,466 | 1,670,686 |
| | **Lower** | 1,319,963 | 1,623,554 | 1,624,740 |

The CIs were calculated for the 99%, 95%, and 90% confidence levels. After comparing the ranges to the base case outputs, only the base case output for the first sub-model that used the CGE 2035 export forecasts without the CPTPP impacts was within the range of the CI at all confidence levels (green shaded). The base case resulted in outputs that are outside of the expected central tendency of the results after uncertainty is introduced. As seen throughout Chapter 4, the base case values tend to be more extreme than the expected range of the central tendency of the simulated outputs. This was also the case for this specific supply chain, and it can be easily confirmed by visually inspecting the mean values and comparing them to the base case outputs. The first sub-model value for the base case is over a million 2015 Canadian dollars off when compared to the mean value. The yearly tonnages for the second sub-model are one order of magnitude away from the mean value. The base case value for the third sub-model is close to the mean value. However, as explained in Section 4.2.1, the dispersion indicates that the observations have a very low standard deviation which makes the CIs narrower.

For this supply chain, similar conclusions cannot be obtained using the mean and base case outputs despite the better dispersion results unless the modeller is only using the outputs of the third sub-model. As explained before, the outputs of the base case greatly differed from the mean outputs for the first two sub-models. This is confirmed by the CI analysis and a visual inspection of the means. Ultimately, even with the smaller dispersion, the base case results were too extreme when compared to the mean outputs simulated after introducing the three sources of input uncertainty.

### 4.3.2. CPTPP Countries Results

The main objective of the preliminary study was to analyze the effects of the CPTPP on Canada's trade infrastructure using the freight model. Therefore, the second targeted analysis focuses on the countries that are signatories of the CPTPP. Nine of the eleven CPTPP countries were included in this targeted analysis (excluding Canada). Brunei was not exclusively defined in the CGE model thus it could not be added without adding non-CPTPP countries to these results.

Defining this supply chain was different than with the US targeted analysis. First, outputs of the nine CPTPP countries were aggregated for all sub-models to obtain the results for one representative country (*l*) for the CPTPP signatories. Then, the supply chain for this representative country with the highest forecasted yearly tonnage in the results for the 2035 forecast that included the CPTPP impacts was selected. The resulting supply chain was food products (*i*), produced in Ontario (j), shipped via rail (*d*) to British Columbia (k), exported to CPTPP representative country (*l*), exported using international mode water (*m*), through the Vancouver Marine and Rail port of clearance (*n*).

After calculating the descriptive statistics, Figure 28 was created. Interestingly, the COVs varied between forecasts (i.e., between the CGE results for 2015, 2035, and 2035 after the CPTPP) for this supply chain. This is different from the trends seen in the disaggregated results (Section 4.1) and in the US targeted analysis (Section 4.3.1), where the results did not vary between CGE forecasts. Unlike the US supply chain results, the figure shows that the dispersion increases at every sub-model for all CGE forecasts. Moreover, for the results using 2015 and 2035 CGE forecasts, the differences of the dispersions between the outputs of the first and second sub-models is smaller (i.e., less sloped lines) than the differences between the outputs of the second and first sub-models (i.e., more sloped lines). These results also follow different trends than those observed on the disaggregated averaged results (see Figure 16). The results using the 2035 CGE forecasts after CPTPP implementation follow a different trend than those using the other two CGE forecasts. This indicates that the uncertainty from the different aggregation schemes of the SCTG codes introduced in the second sub-model caused higher dispersion for the results of the freight model using the CGE forecasts that include the CPTPP policy shocks than when the other forecasts were used. This also suggests that there are dispersion inconsistences for some supply chains between results of different CGE forecasts (2015, 2035, and 2035 with CPTPP), although the mean COVs presented in the disaggregated results (see Figure 16) are consistent between CGE forecasts.

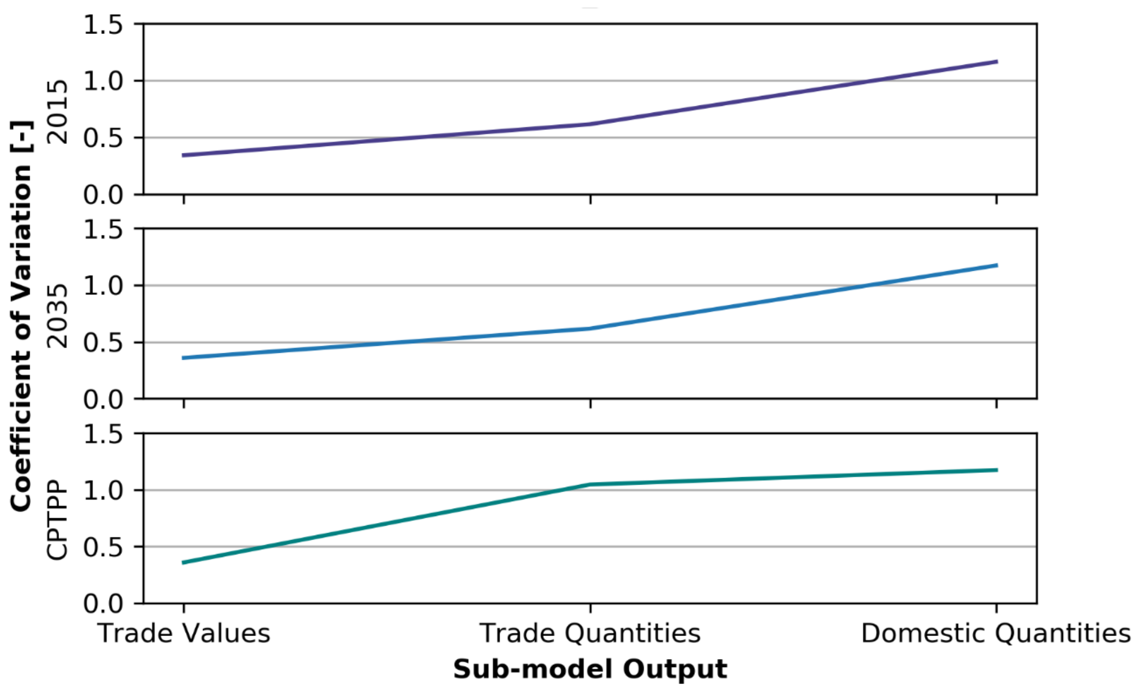


**Figure 28 CPTPP Targeted Analysis COVs for Each Sub-model**

The dispersion values indicate low variance (COV<1) for the first and second sub-model outputs but indicate high variance (COV>1) for the outputs of the third sub-model for results using the 2015 and 2035 CGE forecasts. In contrast, they indicate high variance for the outputs of the second sub-model for results using the 2035 CGE forecasts that included CPTPP impacts. The lower dispersion of the first two sub-models' outputs is harder to justify in this case. One explanation is the aggregation of the countries: Australia, Japan and Mexico (CPTPP signatories) are already large trading partners of Canada. Thus, the same effect that is seen with the US results can be affecting the dispersion of the CPTPP results after the aggregation of the CPTPP countries.

Once again, the assumption of normality for the outputs of the first sub-model was tested before creating the confidence intervals. Figure 29 shows that it is safe to conclude that the outputs follow a normal distribution as the observations generally follow a straight line for the results using all CGE forecasts. The SW test confirmed this conclusion for the same set up as the one presented in the US targeted analysis. The test yielded a p-value of 0.260 which is much higher than a significance level of 0.05 or even 0.1. This means that there is insufficient evidence to reject the $H_0$ and the data are normally distributed.

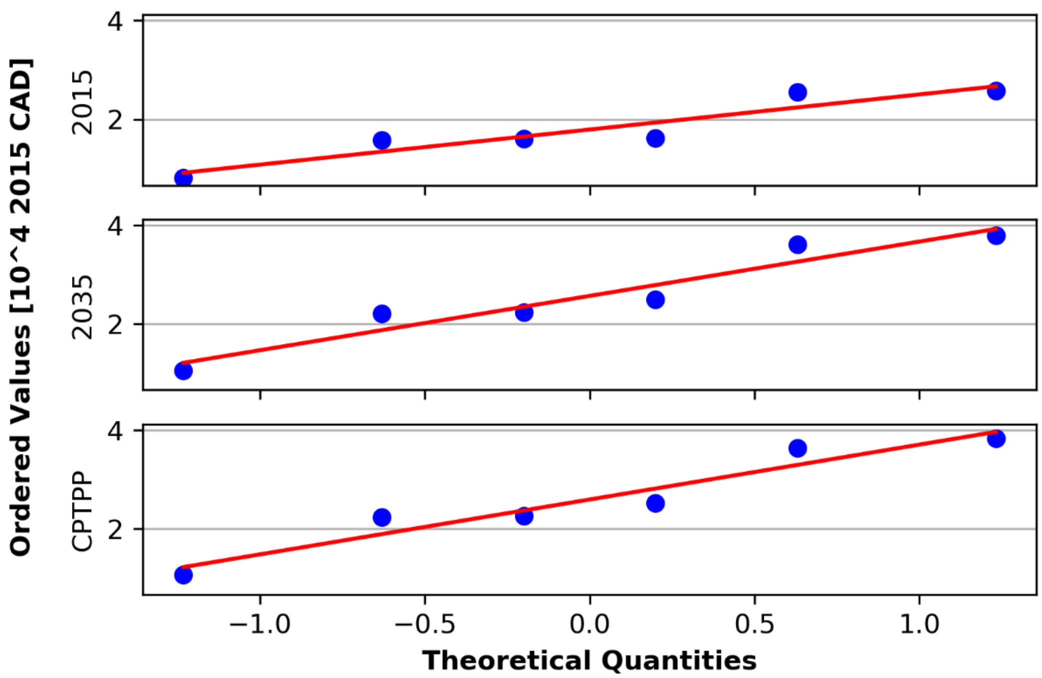


**Figure 29 NPP for the Outputs of First Sub-Model (CPTPP)**

The results are tabulated in Table 43 for the output of the first sub-model ($z_{food\_products,Ontario,British\_Columbia,CPTPP\_countries,water,Vacouver\text{-}Marine\_and\_rail}$) in yearly 2015 Canadian dollars, in Table 44 for the output of the second sub-model ($t_{food\_products,Ontario,British\_Columbia,CPTPP\_countries,water,Vacouver\text{-}Marine\_and\_rail}$), and Table 45 for the output of the third sub-model ($t_{Ontario,British\_Columbia,rail}$), both in yearly tonnes.

**Table 43 Results of the First Sub-Model for a Single Supply Chain (CPTPP)**

| Forecast Year | | 2015 | 2035 | CPTPP |
|---|---|---|---|---|
| **Base** | | 25,800 | 38,002 | 38,344 |
| **Mean** | | 17,931 | 25,704 | 25,935 |
| **COV** | | 0.341 | 0.359 | 0.359 |
| **90% CI** | **Upper** | 22,963 | 33,295 | 33,601 |
| | **Lower** | 12,899 | 18,114 | 18,269 |
| **95% CI** | **Upper** | 24,351 | 35,388 | 35,715 |
| | **Lower** | 11,512 | 16,021 | 16,156 |
| **99% CI** | **Upper** | 28,000 | 40,893 | 41,275 |
| | **Lower** | 7,862 | 10,516 | 10,595 |

**Table 44 Results of the Second Sub-Model for a Single Supply Chain (CPTPP)**

| Forecast Year | | 2015 | 2035 | CPTPP |
|---|---|---|---|---|
| **Base** | | 255,333 | 352,089 | 4,041,251 |
| **Mean** | | 105,178 | 142,973 | 926,414 |
| **COV** | | 0.614 | 0.616 | 1.044 |
| **90% CI** | **Upper** | 127,770 | 173,778 | 1,264,930 |
| | **Lower** | 82,585 | 112,167 | 587,898 |
| **95% CI** | **Upper** | 132,447 | 180,155 | 1,335,006 |
| | **Lower** | 77,908 | 105,790 | 517,823 |
| **99% CI** | **Upper** | 142,185 | 193,432 | 1,480,906 |
| | **Lower** | 68,170 | 92,513 | 371,922 |

**Table 45 Results of the Third Sub-Model for a Single Supply Chain (CPTPP)**

| Forecast Year | | 2015 | 2035 | CPTPP |
|---|---|---|---|---|
| **Base** | | 93,812 | 126,062 | 126,933 |
| **Mean** | | 22,013 | 29,393 | 29,588 |
| **COV** | | 1.163 | 1.171 | 1.172 |
| **90% CI** | **Upper** | 25,280 | 33,787 | 34,013 |
| | **Lower** | 18,746 | 24,999 | 25,164 |
| **95% CI** | **Upper** | 25,913 | 34,638 | 34,869 |
| | **Lower** | 18,113 | 24,149 | 24,307 |
| **99% CI** | **Upper** | 27,160 | 36,315 | 36,558 |
| | **Lower** | 16,866 | 22,472 | 22,618 |

None of the base case outputs were within the ranges of the CIs for the 99%, 95%, and 90% confidence levels. A visual inspection of the tables showed that all the base case values were higher than the mean outputs of the repeated simulation for all sub-models and all CGE forecasts. Some of the base case values were orders of magnitudes higher than the mean outputs. In particular, the base case trade quantity (output of second sub-model) was over 4 million yearly tonnes while the same value was only over 900 thousand for the mean trade quantity. This further confirms the trend that the base case data tend to yield more extreme results than the expected central tendency of the repeated simulation results.

Both targeted analyses showed that similar conclusions could not be obtained using the mean and base case outputs for these supply chains. The dispersion exhibited by both analyses was different with the results of the US targeted analysis demonstrating very low variance for all sub-models and the results for the CPTPP targeted analysis showing dispersions closer to one and above one (outputs of third sub-model). Moreover, both analyses showed poor results in their CI analyses.

### 4.4. Summary of Case Study Major Findings

In general, the base case data generated results that tended to be more extreme than the mean of the simulated population after the sources of uncertainty were introduced. This was evident through the construction of the confidence intervals for the disaggregated results (Section 4.1), for the aggregated results (Section 4.2), and even more obvious for both single supply chains examined in the targeted analyses (Section 4.3). The fractions of total outputs, for outputs of all sub-models, were not greater than 50% for any confidence level (99%, 95%, 90%) for all of the type of results studied. This means that, in general, regardless of aggregation or type of output studied, the base case freight model tends to yield outputs that fall outside of the expected range of the central tendency of the outputs created using repeated simulations when adding the three input sources of uncertainty.

The results of the dispersion were more varied. The disaggregated results showed that on average the dispersion of the outputs of all three sub-models indicate high variance (COV>1). However, for the outputs of the last sub-model over 50% of the observed COVs indicated low variance. For these results, the dispersion of the disaggregated outputs increased from the first to the second sub-model and decreased from the second to the third on average. This behaviour was expected, as sources of uncertainty are introduced at each sub-model, increasing the mean dispersion, but the supply chains are highly aggregated from the second to the third sub-model lowering mean dispersion. Interestingly, the targeted analyses, which used the results for two disaggregated singly supply chains, yielded COV values that indicated low variance for the first two sub-models and a similar result to the mean COV of the disaggregated results for the third sub-model. This suggests that the freight model performs better, in terms of dispersion, for these two supply chains than it performs on average after the input uncertainty is introduced. This was true for results generated using all the CGE forecasts except for the CPTPP supply chain that used the results of the CGE forecast for 2035 including CPTPP export impacts. For the aggregated gateways and domestic summaries, the dispersion generally indicated low variance with a few exceptions and even fewer cases with extremely high dispersion (see Table 32). The dispersion was generally lower in the gateway summaries than in the domestic summaries. This was expected as the gateway summary results are more aggregated than the domestic summary results. In addition, the domestic summary results are affected by all three sources of uncertainty (supply chain shares' base year, aggregation scheme for SCTG codes for value-weight ratios, and domestic mode shares' base year), whereas the gateway summaries are affected only by the first two.

The results for the outputs of the aggregated ports of clearance were promising. Visual comparisons showed that a decent number of ports identified in the top ten by the base case outputs were also identified by the mean outputs of the repeated simulations. The $RRE_{wa}$ values revealed the importance of considerations selecting base cases for these aggregated port of clearance results, if all available data are not used and averaged, since the resulting top ten lists may vary greatly.

In general, most of the same major conclusions could be confirmed using the mean results as in the preliminary study's base case. There were a few exceptions. Despite the poor results of the CIs analysis and high variance of the disaggregated outputs, the results were still able to produce similar conclusions to the base case for the most part. This is in part due to the aggregation of the outputs needed to infer the major conclusions. However, there are a few major conclusions that were different. Thus, the freight model was sensitive to the input uncertainty even after highly aggregating the outputs.

The targeted analyses yielded differences between the US single supply chain and the CPTPP signatories' single supply. The dispersion results for the US targeted analysis indicate very low variance for all sub-models, while the results for the CPTPP targeted analysis indicate low variance (however the COVs were closer to 1) for the outputs of the first two sub-models and high variance for the third sub-model outputs. This may be because the US and some of the CPTPP countries are already large Canadian trade partners. More utilized supply chains likely exhibit less variation from dataset to dataset because they are already utilized. However, the CPTPP also includes countries that are not already large Canadian trade partners. This may explain the higher dispersion observed for the CPTPP targeted analysis in the outputs of the second sub-model (trade quantities in yearly tonnages) when using the results of the CGE forecast that includes the impacts of the CPTPP. The increase in dispersion captures the shifts in the amounts of commodities moving through certain (less utilized) supply chains.

Lastly, this thesis also briefly demonstrated the importance of checking the assumption of normality when utilizing parametric statistical tests. The results of the CI analysis changed drastically when comparing the outputs where the normality assumption was not checked (Figure 20) versus the outputs when it was (Figure 21) at the 95% and 90% confidence levels.

# Chapter 5. Conclusions and Recommendations

This thesis developed and implemented a framework to analyze the effects and propagation of input uncertainty on the uncertainty of the outputs in commodity-based freight demand models. The first objective was to review the literature on freight demand modelling to identify and classify research and practical efforts on available modelling techniques. The second objective was to review the methodologies used in uncertainty analysis of transportation demand models (passenger and freight). The third objective was to develop a framework to study and quantify input uncertainty in commodity-based freight demand models. The last objective was to quantify the propagation of uncertainty due to inputs on the model developed by Bachmann (2017) and Jahangiriesmaili et al. (2018) to evaluate the freight impacts of FTAs in Canada using the CPTPP as a case study.

The first two objectives were fulfilled by reviewing the literature and the following conclusions were drawn. There was disagreement in the literature on the terminology used to describe and categorize freight demand models; however, it was concluded that the terminology based on the unit of reference for demand generation was the most widely used. The literature also confirmed that the most widely used type of freight demand model in practice is the commodity-based model. This was less apparent in the Canadian review than in the United States review. However, the Canadian state-of-practice review was not comprehensive due to the limited information available publicly. Lastly, two important gaps were identified in the literature review regarding uncertainty analysis in freight demand models. First, there was no formal approach specified studying the uncertainty in freight demand models, and only one ad-hoc study by Westing et al. (2016). Second, there was no analysis studying the propagation of uncertainty through successive sub-models in freight demand models. An example of this type of analysis on a passenger demand model was found in Zhao and Kockelman (2002).

The framework developed (objective three) consisted of five steps based on best practices identified through the literature and knowledge of statistical analyses. The framework was developed specifically to study the uncertainty due to inputs on outputs of commodity-based freight demand models. Only input uncertainty was considered, as supposed to also considering model uncertainty, because the literature has shown that input uncertainty is often a greater contributor to uncertainty of the outputs than model uncertainty (de Jong et al., 2007; Rasouli & Timmermans, 2012). Moreover, the same or similar datasets are used as inputs for multiple commodity-based freight demand models, whereas uncertainty due to model specification/calibration is more specific to the development of each model. In the first step, the sources of input uncertainty, their related outputs, and available data are specified. In the second step, the distributions, or the forms of the variation for the sources of uncertainty are identified. In the third step, repeated simulations are used to generate a set of outputs after introducing the variations in the sources of uncertainty. Finally, in the last two steps, the uncertainty of the outputs is quantified and analyzed.

The fourth objective was to apply the framework to a case study. Three sources of input uncertainty were identified with their respective outputs and the available data. The first source of uncertainty was the supply chain shares calculated using CBSA export data. There were 6 years of data available (2010-2015). The second source of uncertainty was the SCTG sector code aggregation used to calculate the value-weight ratios. Four aggregation schemes were used for the level of sectoral detail by SCTG code (5-digit, 4-digit, 3-digit, and 2-digit). The last source of uncertainty was the domestic mode shares calculated using CFAF data. There were 7 years of data available (2011-2017). Due to the successive nature of the sub-models, the first sub-model output was affected only by the first source of uncertainty, the second was affected by both the first and second source of uncertainty, and the third was affected by all three. The simulations were ran accordingly using all available data and the rest of the framework was applied.

The case study yields interesting and important findings for freight modellers. In the disaggregated outputs, all sub-model outputs exhibit high variance (COV>1) *on average*, with the COVs of the domestic movements being close to one, as they are highly aggregated in comparison to the outputs of the first two sub-models. Most major conclusions using the aggregated results agree between the illustrative base case and the simulated outputs despite the tendency to high variances (COV>1 on average) observed on the disaggregated results and poor results of the CI analysis. The framework also reveals that specific movements where the results of the base case may not be highly accurate (e.g., the aggregate domestic movements via truck from Maritime provinces to Western provinces in the results using CGE forecasts for 2035 including CPTPP impacts). The analysis on the ports of clearance revealed the importance of considerations selecting base cases for these results, if all available data are not used, since the resulting top ten lists may vary greatly. In conclusion, the framework generates insight on the accuracy of the case study model, and it highlights the specific instances where the modeller needs to be more cautious of the results when using only point data, as in the illustrative base case. All major conclusions are summarized below:

- In general, the base case data generated results that tended to be more extreme than the mean of the simulated population after the sources of uncertainty were introduced.
- The results of the dispersion were more varied with a tendency to high variances in the disaggregated results and lower variances in the aggregated results.
- The results for the outputs of the aggregated ports of clearance showed some consistency between averaged results and base case but the poor rank error results highlight the importance of carefully choosing a base case since the top ten ranked ports vary greatly between simulation runs.
- In general, most of the same major conclusions could be confirmed using the mean results as in the preliminary study's base case with a few exceptions.
- The targeted analyses yielded differences between the US single supply chain and the CPTPP signatories' single supply likely due to the less utilized supply chains (small Canadian trade partners) included in the latter.
- It is important to check the assumption of normality when utilizing parametric statistical tests.

## 5.1. Limitations and Future Research

The limitations of this study are mainly based on the scope boundaries. First the scope did not include uncertainty due to model specification/estimation. Therefore, it is assumed that the model to which the framework is applied has been perfectly specified and estimated. However, often, there are several assumptions within the process of model development. These assumptions are likely to induce some additional error. Second, the scope did not include the study of uncertainty in activity-based models. Activity-based models are different from trip-based and commodity-based models in that they are stochastic. For this reason, the propagation of their uncertainty deserves its own framework. Moreover, the literature shows a greater focus on quantifying the effects of stochastic simulation error as opposed to input uncertainty or other forms of model uncertainty (i.e., specification and estimation) (Castiglione et al., 2003; Cools et al., 2011; Gibb & Bowman, 2007; Lawe et al., 2009). It is also important to note that multiple authors in the literature concluded that travel demand modelling is trending towards adopting more activity-based modelling techniques (Chow et al., 2010; Liedtke & Schepperle, 2004; National Cooperative Highway Research Program, 2008; Nuzzolo et al., 2013; Wisetjindawat et al., 2012).

Other limitations and possible future research topics were found in the unexplored gaps of the literature. First, a similar study can be conducted using different, more systematic, variations instead of Monte Carlo simulation such as factorial designs, probabilistic designs, etc. Second, a similar study can be conducted testing the assumptions of the probability distributions for inputs. For example, simulating results assuming other distributions than normal or multivariate normal and comparing the results. Third, the use of nonparametric statistical tests can also be explored and compared to their parametric equivalents. Forth, a similar study can be conducted using a more educated approach to selecting variables (inputs) to vary in the repeated simulations (i.e., which variables affect the outputs the most based on practical/outside experience and knowledge). Last, in the context of this specific work, a next step could be using a sensitivity analysis to explore which of the three sources of uncertainty explored affect the outputs the most.

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## Appendix A – 2035 Forecast Mean COVs for the Outputs of Each Sub-model

### Table A. 1 Naming Convention for Appendix A Tables

| No. | Country of Export (l) | Commodity/Sector (i) | Subnational Region O-D (j,k) |
|---|---|---|---|
| **1** | EU28 | Rice | British Columbia |
| **2** | USA | Wheat & Cereals | Alberta |
| **3** | Australia | Fruit & Vegetables | Saskatchewan |
| **4** | Rest of Southeast Asia | Oil Seeds & Vegetable Oils | Manitoba |
| **5** | Chile | Sugar | Ontario |
| **6** | Japan | Other Farming | Quebec |
| **7** | Malyasia | Dairy | New Brunswick |
| **8** | Mexico | Forestry | Nova Scotia |
| **9** | New Zealand | Fishing | Newfoundland/Labrador |
| **10** | Peru | Fossil Fuels | Prince Edward Is. |
| **11** | Singapore | Mineral Products | Yukon, Northwest Territories, Nunavut |
| **12** | Vietnam | Beef | |
| **13** | China | Pork & Poultry | |
| **14** | Korea | Food Products | |
| **15** | India | Beverages & Tobacco | |
| **16** | Thailand | Textiles & Apparel | |
| **17** | Philippines | Leather Products | |
| **18** | Indonesia | Wood Products | |
| **19** | Colombia | Chemical, Rubber & Plastics | |
| **20** | Central America (Costa Rica, Panama) | Metals & Metal Products | |
| **21** | Hong Kong | Automotive | |
| **22** | Other EFTA (Iceland, Leichtenstein) | Transport Equipment | |
| **23** | Israel | Electronic Equipment | |
| **24** | Pakistan | Machinery & Equipment | |
| **25** | Other South America (Paraguay and Uruguay | Other Manufactures | |
| **26** | Switzerland | Other Services | |
| **27** | Norway | Construction[1] | |
| **28** | Turkey | Trade[1] | |
| **29** | Taiwan | Transport[1] | |
| **30** | Kenya | Communication[1] | |
| **31** | Tanzania | Financial Services[1] | |
| **32** | Uganda | Business Services | |
| **33** | Rwanda | Recreation | |
| **34** | Rest of East Africa | | |
| **35** | Ethiopia | | |
| **36** | Mozambique | | |
| **37** | SACU | | |
| **38** | Other TFTA | | |
| **39** | ROW | | |

[1]Service industries are omitted from this analysis as there were no records, such as CBSA, capturing their shares.

**Table A. 2 2035 Forecast Mean COVs for the Outputs ($s_{ijklmn}$) of the First Sub-model Averaged Over ($j,k,m,n$)**

| l,i | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26[1] | 32 | 33 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 1.8 | 1.7 | 1.7 | 1.8 | 1.6 | 1.6 | 1.8 | 1.7 | 1.7 | 1.7 | 1.7 | 1.8 | 1.8 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.6 | 1.7 | 1.7 | 1.7 | 1.6 | 2.0 | 1.6 | 1.7 |
| **2** | 1.5 | 1.4 | 1.2 | 1.3 | 1.3 | 1.2 | 1.5 | 1.3 | 1.3 | 1.2 | 1.2 | 1.4 | 1.3 | 1.1 | 1.3 | 1.3 | 1.3 | 1.0 | 1.0 | 1.2 | 1.2 | 1.4 | 1.3 | 1.2 | 1.3 | 1.6 | 1.7 | 1.5 |
| **3** | 2.2 | 1.6 | 1.8 | 1.7 | 1.8 | 1.7 | 1.7 | 1.9 | 1.9 | 1.5 | 1.7 | 1.7 | 1.8 | 1.6 | 1.8 | 1.7 | 1.8 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 2.1 | 2.2 | 1.7 |
| **4** | 2.2 | [2] | 1.9 | 1.4 | 2.2 | 2.1 | | 2.2 | 1.8 | 2.0 | 2.0 | 2.2 | 2.2 | 1.3 | 2.2 | 1.8 | 1.9 | 1.9 | 1.8 | 1.8 | 1.8 | 2.0 | 1.7 | 1.7 | 1.7 | 1.6 | 2.2 | |
| **5** | 1.4 | 1.7 | 1.7 | 1.8 | 2.0 | 1.7 | 1.9 | 1.2 | 1.6 | 1.8 | 1.9 | 1.8 | 1.8 | 1.7 | 2.1 | 1.8 | 1.8 | 1.8 | 1.7 | 1.7 | 1.8 | 1.8 | 1.8 | 1.7 | 1.8 | 2.2 | 2.2 | 2.1 |
| **6** | 2.2 | 1.9 | 1.7 | 1.6 | 1.7 | 1.6 | 1.9 | 1.5 | 1.6 | 1.6 | 1.8 | 1.6 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.8 | 1.7 | 1.7 | 1.6 | 1.6 | 1.7 | 1.9 | 1.6 | 1.9 |
| **7** | 1.4 | 1.6 | 1.7 | 1.7 | 2.2 | 1.6 | 1.9 | 1.8 | 1.5 | 1.7 | 1.8 | 1.6 | 1.8 | 1.7 | 1.7 | 1.8 | 1.7 | 1.7 | 1.7 | 1.7 | 1.9 | 1.9 | 1.6 | 1.7 | 1.8 | 2.2 | 2.2 | 1.7 |
| **8** | | 1.7 | 1.7 | 1.7 | 1.8 | 1.7 | 1.7 | 2.0 | 2.2 | 1.7 | 1.8 | 1.7 | 1.8 | 1.7 | 1.9 | 1.8 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.8 | 1.7 | 1.8 | 2.2 | 2.0 | 1.9 |
| **9** | | 2.1 | 1.7 | 1.6 | 1.8 | 1.7 | 1.9 | 2.1 | 1.5 | 1.9 | 1.7 | 1.8 | 1.8 | 1.6 | 1.8 | 1.7 | 1.7 | 1.8 | 1.6 | 1.8 | 1.7 | 1.8 | 1.7 | 1.7 | 1.7 | 2.2 | 1.8 | 1.8 |
| **10** | | 1.8 | 1.6 | 1.6 | 2.2 | 1.4 | 1.9 | 1.8 | 1.0 | 1.8 | 1.9 | 2.0 | 1.9 | 1.6 | 2.0 | 1.8 | 1.8 | 1.8 | 1.7 | 1.7 | 1.9 | 1.9 | 1.9 | 1.8 | 1.8 | 2.0 | 2.2 | 1.4 |
| **11** | | 1.4 | 1.9 | 1.8 | 1.6 | 1.7 | 1.6 | 2.1 | 1.7 | 1.9 | 1.8 | 1.7 | 1.6 | 1.7 | 1.6 | 1.8 | 1.7 | 1.7 | 1.8 | 1.8 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 2.1 | 1.8 |
| **12** | 2.2 | 1.6 | 2.0 | 1.8 | 2.2 | 1.9 | 1.8 | 2.0 | 1.9 | 1.9 | 1.8 | 1.7 | 1.7 | 1.6 | 1.9 | 1.8 | 2.0 | 1.7 | 1.7 | 1.7 | 1.8 | 1.8 | 1.7 | 1.7 | 1.8 | 1.5 | 2.2 | |
| **13** | 2.2 | 1.8 | 1.8 | 1.8 | 1.7 | 1.8 | 1.8 | 1.5 | 1.7 | 1.5 | 1.7 | 1.6 | 1.7 | 1.7 | 1.8 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.8 | 1.7 | 1.7 | 1.7 | 1.7 | 1.9 | 2.0 | 1.7 |
| **14** | 2.2 | 2.0 | 1.7 | 1.7 | 1.6 | 1.7 | 1.8 | 1.7 | 1.7 | 1.5 | 1.8 | 1.7 | 1.5 | 1.7 | 1.6 | 1.8 | 1.7 | 1.8 | 1.7 | 1.7 | 1.7 | 1.8 | 1.7 | 1.7 | 1.7 | 1.9 | 1.5 | 1.7 |
| **15** | 2.2 | 2.1 | 1.7 | 1.9 | 1.7 | 1.7 | 1.9 | 2.0 | 2.2 | 1.9 | 1.7 | 1.0 | 1.8 | 1.7 | 1.7 | 1.8 | 1.8 | 1.7 | 1.7 | 1.8 | 1.7 | 1.8 | 1.7 | 1.7 | 1.8 | 2.0 | 2.0 | 2.0 |
| **16** | 1.6 | 1.6 | 1.7 | 1.8 | 1.6 | 1.7 | 1.8 | 2.1 | 1.9 | 1.6 | 1.7 | 1.4 | 1.9 | 1.7 | 1.7 | 1.8 | 1.8 | 1.7 | 1.6 | 1.7 | 1.7 | 1.8 | 1.7 | 1.6 | 1.7 | 2.0 | | 2.0 |
| **17** | 1.0 | 1.4 | 1.6 | 1.7 | 2.1 | 2.0 | 1.7 | 2.0 | 2.0 | 1.6 | 1.8 | 1.6 | 1.7 | 1.6 | 1.7 | 1.9 | 1.9 | 1.7 | 1.7 | 1.8 | 1.7 | 1.8 | 1.7 | 1.7 | 1.8 | 2.2 | 2.0 | 2.1 |
| **18** | | 1.7 | 1.8 | 1.8 | 1.8 | 2.0 | 1.9 | 2.0 | 1.6 | 1.8 | 1.9 | 2.0 | 1.7 | 1.6 | 2.1 | 1.8 | 1.8 | 1.7 | 1.8 | 1.8 | 2.0 | 1.7 | 1.7 | 1.7 | 1.8 | 2.2 | 2.2 | 1.9 |
| **19** | | 1.6 | 1.7 | 1.8 | 2.2 | 1.8 | 1.9 | 1.8 | 1.6 | 1.8 | 1.7 | 1.8 | 1.7 | 1.6 | 1.7 | 1.8 | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 | 1.8 | 1.8 | 1.7 | 1.7 | 2.2 | 2.2 | 2.0 |
| **20** | 2.2 | 1.7 | 1.7 | 1.6 | 2.2 | 1.8 | 1.9 | 1.9 | 0.0 | 1.7 | 1.8 | 1.8 | 1.8 | 1.7 | 1.8 | 1.8 | 1.8 | 1.7 | 1.6 | 1.9 | 1.7 | 1.9 | 1.8 | 1.8 | 1.8 | 1.5 | 2.0 | 2.0 |
| **21** | 2.2 | 1.9 | 1.9 | 1.7 | 1.5 | 1.7 | 1.6 | 1.9 | 1.7 | 1.9 | 1.8 | 1.7 | 1.6 | 1.7 | 1.8 | 1.7 | 1.7 | 1.7 | 1.5 | 1.8 | 1.7 | 1.7 | 1.6 | 1.7 | 1.7 | 1.9 | 1.0 | 1.7 |
| **22** | | 2.0 | 1.7 | 1.8 | 1.8 | 2.0 | 1.1 | 2.2 | 1.6 | 2.1 | 1.8 | | 2.0 | 1.7 | 2.2 | 1.8 | 1.8 | 1.8 | 1.7 | 1.7 | 1.9 | 1.9 | 1.7 | 1.7 | 1.7 | 2.2 | | 2.2 |
| **23** | 2.2 | 1.7 | 1.6 | 1.9 | 1.5 | 1.8 | 2.2 | 1.9 | 1.2 | 1.6 | 1.9 | | 1.8 | 1.6 | 1.7 | 1.7 | 1.9 | 1.8 | 1.7 | 1.8 | 1.8 | 1.9 | 1.7 | 1.6 | 1.7 | 2.2 | 0.9 | 1.8 |
| **24** | 2.2 | 2.0 | 1.8 | 1.8 | | 1.9 | 2.1 | 1.9 | 1.0 | 1.9 | 1.9 | | 2.0 | 1.7 | | 1.8 | 1.8 | 1.7 | 1.7 | 1.8 | 1.8 | 1.7 | 1.6 | 1.7 | 1.8 | 2.2 | | 1.0 |
| **25** | | 1.7 | 1.6 | 1.7 | 2.2 | 1.4 | 1.8 | 0.7 | | 1.9 | 1.8 | 1.9 | 1.8 | 1.8 | 1.8 | 1.8 | 1.8 | 1.8 | 1.8 | 1.8 | 1.7 | 1.9 | 1.8 | 1.8 | 1.8 | 2.2 | 2.2 | 2.0 |
| **26** | 2.2 | 1.7 | 1.8 | 1.7 | 1.5 | 1.7 | 2.2 | 1.7 | 1.8 | 1.7 | 1.9 | 1.7 | 1.4 | 1.7 | 1.7 | 1.7 | 1.7 | 1.8 | 1.7 | 1.8 | 1.8 | 1.7 | 1.7 | 1.7 | 1.7 | 2.2 | 1.1 | 1.9 |
| **27** | | 2.0 | 1.9 | 1.8 | 1.8 | 1.8 | 1.0 | 2.2 | 1.8 | 1.6 | 1.8 | | 1.9 | 1.5 | 1.8 | 1.8 | 1.8 | 1.7 | 1.8 | 1.8 | 1.8 | 1.8 | 1.7 | 1.7 | 1.6 | | 1.8 | 1.9 |
| **28** | 2.2 | 1.9 | 1.8 | 1.9 | 1.6 | 1.5 | 1.8 | 2.1 | 2.2 | 1.7 | 1.7 | 2.2 | 1.9 | 1.8 | 1.6 | 1.7 | 1.8 | 1.7 | 1.6 | 1.8 | 1.6 | 1.8 | 1.6 | 1.7 | 1.7 | | 2.2 | 2.0 |
| **29** | 2.2 | 1.8 | 1.7 | 1.7 | 1.4 | 1.8 | 1.8 | 1.7 | 1.7 | 1.6 | 1.6 | 1.6 | 1.7 | 1.6 | 1.7 | 1.7 | 1.7 | 1.8 | 1.6 | 1.7 | 1.8 | 1.7 | 1.7 | 1.7 | 1.7 | 1.9 | 1.5 | 1.9 |
| **30** | 2.2 | 1.6 | 1.1 | 1.4 | 2.2 | 1.1 | | | | 2.1 | 2.0 | | 1.5 | 1.9 | 2.2 | 1.9 | 1.8 | 1.9 | 1.8 | 1.9 | 1.9 | 1.8 | 1.7 | 1.8 | 1.9 | | | 1.8 |
| **31** | | 1.5 | 1.8 | 2.2 | | 1.0 | | | 2.2 | 2.1 | 1.7 | 2.2 | 2.2 | 1.4 | 2.0 | 1.8 | 1.9 | 1.9 | 1.8 | 1.9 | 1.8 | 1.9 | 1.9 | 1.8 | 1.9 | 2.2 | | |
| **32** | | 1.8 | 1.8 | 2.2 | | 1.3 | 2.2 | 2.2 | | | 2.1 | | 2.2 | 1.7 | 2.2 | 2.0 | 2.0 | 2.0 | 1.9 | 1.9 | 2.0 | 1.9 | 1.9 | 1.9 | 1.9 | 2.2 | | |

| l,i | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26[1] | 32 | 33 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **33** | | 2.1 | 2.2 | | | 1.4 | 2.2 | | | | 2.2 | 2.2 | 2.2 | 2.2 | | 2.2 | 1.7 | 1.9 | 1.9 | 2.0 | 1.9 | 1.9 | 1.8 | 2.0 | 2.1 | | | 2.2 |
| **34** | | 1.6 | 1.9 | 2.2 | | 1.6 | 1.6 | 2.2 | 1.8 | 2.0 | 1.9 | 1.9 | 1.9 | 1.9 | 2.2 | 1.8 | 1.9 | 1.9 | 1.8 | 1.8 | 1.7 | 1.8 | 1.8 | 1.8 | 2.0 | 2.2 | 2.2 | 2.2 |
| **35** | | | 1.4 | | | | | | | | 2.2 | | 2.2 | | | 2.1 | 2.1 | 2.1 | 1.9 | 1.9 | 1.9 | 1.9 | 1.8 | 1.8 | 2.0 | | | |
| **36** | | 1.6 | 2.2 | | | 1.0 | | | | 2.2 | 2.1 | 1.5 | 1.8 | 2.2 | 2.2 | 1.7 | 1.8 | 2.0 | 1.9 | 1.9 | 2.0 | 1.9 | 1.8 | 1.9 | 2.0 | | | |
| **37** | 2.2 | 1.9 | 1.8 | 1.7 | 2.0 | 1.8 | 1.9 | 2.1 | 1.8 | 1.8 | 2.0 | 1.9 | 1.8 | 1.7 | 1.9 | 1.8 | 1.8 | 1.8 | 1.7 | 1.8 | 1.8 | 1.9 | 1.7 | 1.7 | 1.8 | 2.0 | 1.6 | 1.9 |
| **38** | 1.4 | 1.9 | 1.7 | 1.9 | 2.1 | 1.8 | 1.8 | 1.4 | 1.5 | 1.9 | 1.9 | 1.7 | 1.8 | 1.6 | 1.8 | 1.8 | 1.8 | 1.7 | 1.8 | 1.8 | 1.7 | 1.8 | 1.8 | 1.7 | 1.9 | 2.2 | 1.8 | 2.0 |
| **39** | 1.6 | 1.7 | 1.7 | 1.8 | 1.7 | 1.8 | 1.8 | 1.7 | 1.8 | 1.7 | 1.7 | 1.7 | 1.7 | 1.6 | 1.7 | 1.7 | 1.8 | 1.7 | 1.6 | 1.7 | 1.7 | 1.8 | 1.7 | 1.7 | 1.7 | 1.9 | 2.0 | 1.9 |

[1]Service sectors (27-31) are not shown as these values are nan (not a number) since they all have a value of zero in the model outputs (due to lack of records on service sector movements to create shares).

[2]Grey boxes show nan values which means that the average of the commodity flows was zero for these supply chains.

**Table A. 3 2035 Forecast Mean COVs for the Outputs ($t_{ijklmn}$) of the Second Sub-model Averaged Over ($j,k,m,n$)**

| l,i | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26[1] | 32 | 33 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 2.0 | 1.8 | 1.9 | 1.8 | 1.6 | 2.2 | 1.9 | 2.2 | 1.8 | 1.8 | 2.2 | 1.8 | 1.8 | 1.8 | 1.9 | 1.9 | 1.8 | 1.8 | 1.8 | 1.9 | 1.7 | 2.1 | 2.1 | 1.8 | 1.9 | 2.3 | 2.0 | 2.2 |
| **2** | 1.7 | 1.5 | 1.4 | 1.3 | 1.4 | 1.5 | 1.6 | 1.6 | 1.6 | 1.3 | 1.6 | 1.5 | 1.4 | 1.2 | 1.3 | 1.4 | 1.4 | 1.1 | 1.1 | 1.3 | 1.3 | 1.7 | 1.8 | 1.3 | 1.3 | 1.9 | 2.3 | 2.0 |
| **3** | 2.4 | 1.6 | 2.0 | 1.7 | 1.8 | 2.2 | 1.8 | 2.2 | 2.4 | 1.6 | 2.2 | 1.7 | 1.8 | 1.8 | 1.9 | 2.0 | 1.9 | 1.8 | 1.8 | 1.9 | 1.8 | 2.1 | 2.2 | 1.8 | 1.9 | 2.5 | 2.5 | 2.2 |
| **4** | 2.4 | [2] | 2.1 | 1.4 | 2.3 | 2.7 | | 2.6 | 2.0 | 2.0 | 2.6 | 2.3 | 2.3 | 1.4 | 2.5 | 2.0 | 2.0 | 2.1 | 1.9 | 2.1 | 1.9 | 2.3 | 2.2 | 1.9 | 1.9 | 1.9 | 2.3 | |
| **5** | 1.6 | 1.8 | 1.9 | 1.8 | 2.0 | 2.1 | 2.1 | 1.5 | 1.8 | 1.9 | 2.2 | 1.9 | 1.8 | 1.8 | 2.2 | 2.0 | 1.8 | 2.0 | 1.8 | 1.9 | 1.9 | 2.2 | 2.4 | 1.8 | 2.0 | 2.6 | 2.6 | 2.9 |
| **6** | 2.4 | 1.9 | 2.0 | 1.6 | 1.7 | 1.8 | 2.0 | 1.8 | 1.8 | 1.9 | 2.3 | 1.6 | 1.7 | 1.9 | 1.9 | 2.0 | 1.8 | 1.8 | 1.7 | 2.0 | 1.9 | 2.0 | 2.2 | 1.8 | 2.0 | 2.3 | 2.6 | 2.4 |
| **7** | 1.6 | 1.6 | 1.8 | 1.7 | 2.2 | 2.2 | 2.0 | 2.1 | 1.8 | 2.0 | 2.3 | 1.7 | 1.9 | 1.9 | 2.0 | 2.0 | 1.8 | 1.8 | 1.8 | 1.8 | 2.0 | 2.3 | 2.3 | 1.8 | 2.1 | 2.6 | 2.3 | 2.2 |
| **8** | | 1.8 | 1.8 | 1.7 | 1.9 | 2.1 | 1.8 | 2.2 | 2.9 | 1.8 | 2.2 | 1.7 | 1.8 | 1.9 | 2.0 | 1.9 | 1.8 | 1.8 | 1.8 | 1.9 | 1.8 | 2.0 | 2.2 | 1.8 | 2.0 | 2.6 | 2.4 | 2.4 |
| **9** | | 2.1 | 2.0 | 1.6 | 1.9 | 2.3 | 2.0 | 2.4 | 2.0 | 2.0 | 2.2 | 1.8 | 1.8 | 1.7 | 1.9 | 2.0 | 1.8 | 1.9 | 1.7 | 2.0 | 1.9 | 2.1 | 2.3 | 1.8 | 2.0 | 2.6 | 1.9 | 2.3 |
| **10** | | 1.8 | 1.7 | 1.7 | 2.3 | 1.8 | 2.0 | 2.2 | 1.2 | 1.9 | 2.3 | 2.1 | 1.9 | 1.8 | 2.1 | 2.0 | 1.9 | 1.9 | 1.8 | 1.9 | 2.0 | 2.3 | 2.6 | 1.9 | 1.9 | 2.3 | 2.3 | 2.2 |
| **11** | | 1.5 | 2.3 | 1.8 | 1.6 | 2.2 | 1.8 | 2.5 | 1.9 | 2.0 | 2.3 | 1.8 | 1.7 | 1.9 | 1.8 | 2.1 | 1.8 | 1.8 | 1.9 | 2.0 | 1.9 | 2.2 | 2.2 | 1.8 | 2.0 | 2.0 | 2.4 | 2.4 |
| **12** | 2.4 | 1.6 | 2.4 | 1.8 | 2.3 | 2.3 | 1.9 | 2.2 | 2.1 | 2.0 | 2.4 | 1.7 | 1.8 | 1.8 | 2.1 | 1.9 | 2.0 | 1.9 | 1.8 | 1.9 | 1.8 | 2.1 | 2.2 | 1.8 | 2.1 | 1.8 | 2.3 | |
| **13** | 2.4 | 1.8 | 2.1 | 1.8 | 1.7 | 2.2 | 1.9 | 1.6 | 1.9 | 1.7 | 2.3 | 1.6 | 1.7 | 1.9 | 2.0 | 1.9 | 1.8 | 1.8 | 1.8 | 1.9 | 1.9 | 2.2 | 2.2 | 1.8 | 2.0 | 2.2 | 2.7 | 2.1 |
| **14** | 2.4 | 2.0 | 1.9 | 1.7 | 1.7 | 2.1 | 1.9 | 1.9 | 1.9 | 1.7 | 2.2 | 1.7 | 1.6 | 1.8 | 1.7 | 2.1 | 1.8 | 1.9 | 1.8 | 1.9 | 1.8 | 2.2 | 2.2 | 1.8 | 2.0 | 2.3 | 1.8 | 2.1 |
| **15** | 2.4 | 2.1 | 1.9 | 1.9 | 1.7 | 2.1 | 1.9 | 2.1 | 3.2 | 1.9 | 2.3 | 1.2 | 1.9 | 2.0 | 1.7 | 2.0 | 1.9 | 1.8 | 1.8 | 2.0 | 1.9 | 2.3 | 2.2 | 1.8 | 2.1 | 2.4 | 2.1 | 2.5 |
| **16** | 1.8 | 1.6 | 1.9 | 1.9 | 1.6 | 2.1 | 1.9 | 2.5 | 2.1 | 1.8 | 2.1 | 1.4 | 2.0 | 2.0 | 1.9 | 1.9 | 1.9 | 1.8 | 1.7 | 1.9 | 1.8 | 2.2 | 2.2 | 1.7 | 2.1 | 2.3 | | 2.7 |
| **17** | 1.1 | 1.4 | 1.8 | 1.7 | 2.1 | 2.3 | 1.7 | 2.5 | 2.1 | 1.7 | 2.3 | 1.6 | 1.7 | 1.7 | 1.8 | 2.1 | 1.9 | 1.8 | 1.8 | 2.1 | 1.8 | 2.2 | 2.3 | 1.8 | 2.1 | 2.6 | 2.8 | 2.6 |
| **18** | | 1.7 | 2.0 | 1.8 | 1.9 | 2.3 | 2.0 | 2.1 | 1.8 | 1.9 | 2.2 | 2.0 | 1.8 | 1.8 | 2.3 | 2.0 | 1.8 | 1.8 | 1.8 | 2.0 | 2.1 | 2.3 | 2.3 | 1.8 | 2.1 | 2.6 | 2.3 | 2.6 |
| **19** | | 1.6 | 1.8 | 1.8 | 2.3 | 2.1 | 2.0 | 2.5 | 1.9 | 1.9 | 2.1 | 1.8 | 1.7 | 1.8 | 1.9 | 1.9 | 1.8 | 1.8 | 1.7 | 1.9 | 1.9 | 2.3 | 2.3 | 1.8 | 1.9 | 2.6 | 2.3 | 2.7 |
| **20** | 2.4 | 1.7 | 1.8 | 1.7 | 2.3 | 2.1 | 2.0 | 2.3 | 0.4 | 1.9 | 2.1 | 1.9 | 1.8 | 1.8 | 1.9 | 2.0 | 1.8 | 1.8 | 1.7 | 2.1 | 1.9 | 2.1 | 2.2 | 1.9 | 2.0 | 1.8 | 2.5 | 2.5 |
| **21** | 2.4 | 1.9 | 2.4 | 1.7 | 1.6 | 2.2 | 1.8 | 2.4 | 1.9 | 2.0 | 2.4 | 1.8 | 1.7 | 1.8 | 2.0 | 1.9 | 1.8 | 1.8 | 1.6 | 2.1 | 1.8 | 1.9 | 2.2 | 1.8 | 2.0 | 2.2 | 1.1 | 2.2 |
| **22** | | 2.0 | 1.9 | 1.9 | 1.9 | 2.6 | 1.4 | 2.5 | 1.7 | 2.1 | 2.3 | | 2.0 | 1.8 | 2.4 | 2.0 | 1.9 | 1.9 | 1.9 | 1.9 | 2.0 | 2.3 | 2.2 | 1.8 | 2.0 | 2.6 | | 2.8 |
| **23** | 2.4 | 1.8 | 1.7 | 1.9 | 1.6 | 2.3 | 2.3 | 2.1 | 1.4 | 1.7 | 2.4 | | 1.9 | 1.8 | 1.8 | 1.9 | 2.0 | 1.9 | 1.8 | 2.0 | 2.0 | 2.3 | 2.2 | 1.8 | 2.1 | 2.6 | 1.5 | 2.3 |
| **24** | 2.3 | 2.0 | 1.9 | 1.7 | | 2.4 | 2.1 | 1.9 | 1.2 | 2.0 | 2.4 | | 2.0 | 1.8 | | 1.9 | 1.9 | 1.8 | 1.8 | 2.0 | 1.9 | 2.2 | 2.1 | 1.8 | 2.1 | 2.6 | | 1.4 |
| **25** | | 1.8 | 1.7 | 1.6 | 2.3 | 1.9 | 1.9 | 1.7 | | 2.1 | 2.3 | 2.0 | 1.8 | 2.0 | 2.0 | 2.0 | 1.8 | 2.0 | 1.9 | 2.0 | 1.8 | 2.3 | 2.3 | 1.9 | 2.1 | 2.6 | 2.3 | 2.6 |
| **26** | 2.3 | 1.8 | 1.9 | 1.8 | 1.6 | 2.1 | 2.3 | 2.3 | 2.0 | 1.9 | 2.4 | 1.8 | 1.4 | 1.9 | 1.9 | 2.0 | 1.8 | 1.9 | 1.8 | 2.1 | 1.9 | 2.1 | 2.2 | 1.8 | 2.0 | 2.6 | 1.4 | 2.4 |
| **27** | | 2.0 | 2.2 | 1.8 | 1.9 | 2.3 | 1.0 | 2.7 | 2.0 | 1.7 | 2.3 | | 1.9 | 1.7 | 1.9 | 2.0 | 1.8 | 1.8 | 1.8 | 2.1 | 1.9 | 2.0 | 2.2 | 1.9 | 1.9 | | 1.9 | 2.4 |
| **28** | 2.4 | 1.9 | 2.0 | 2.0 | 1.7 | 2.0 | 1.9 | 2.3 | 2.4 | 1.9 | 2.2 | 2.3 | 1.9 | 2.1 | 1.7 | 1.9 | 1.9 | 1.8 | 1.7 | 2.0 | 1.7 | 2.2 | 2.1 | 1.8 | 1.9 | | 3.6 | 2.6 |
| **29** | 2.4 | 1.9 | 2.1 | 1.7 | 1.5 | 2.2 | 1.9 | 1.9 | 1.8 | 1.8 | 2.1 | 1.6 | 1.7 | 1.8 | 1.9 | 2.0 | 1.8 | 1.9 | 1.7 | 2.0 | 1.9 | 2.0 | 2.3 | 1.8 | 1.9 | 2.2 | 2.6 | 2.4 |
| **30** | 2.4 | 1.6 | 1.2 | 1.4 | 2.3 | 1.4 | | | | 2.2 | 2.6 | | 1.5 | 1.9 | 2.4 | 2.1 | 1.9 | 2.0 | 1.9 | 2.0 | 2.0 | 2.2 | 2.3 | 1.9 | 2.2 | | | 2.7 |
| **31** | | 1.5 | 1.9 | 2.3 | | 1.7 | | | 2.5 | 2.3 | 2.1 | 2.3 | 2.3 | 1.7 | 2.0 | 1.9 | 2.0 | 2.0 | 1.9 | 2.2 | 1.9 | 2.4 | 2.5 | 1.9 | 2.2 | 2.6 | | |
| **32** | | 1.8 | 1.9 | 2.3 | | 1.9 | 2.4 | 2.6 | | | 2.6 | | 2.3 | 1.8 | 2.3 | 2.1 | 2.0 | 2.1 | 2.0 | 2.1 | 2.2 | 2.3 | 2.5 | 1.9 | 2.1 | 2.6 | | |

| l,i | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26[1] | 32 | 33 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **33** | | 2.1 | 2.8 | | | 1.6 | 2.3 | | | | 2.9 | 2.3 | 2.3 | 2.5 | | 2.3 | 1.7 | 2.0 | 2.0 | 2.2 | 2.0 | 2.3 | 2.4 | 2.1 | 2.3 | | | 2.8 |
| **34** | | 1.6 | 1.9 | 2.3 | | 2.1 | 1.7 | 2.3 | 2.0 | 2.1 | 2.6 | 2.0 | 1.9 | 2.0 | 2.3 | 2.0 | 2.0 | 2.1 | 1.9 | 2.0 | 1.9 | 2.2 | 2.4 | 1.9 | 2.3 | 2.6 | 2.3 | 2.8 |
| **35** | | | 1.4 | | | | | | | | 2.5 | | 2.3 | | | 2.4 | 2.2 | 2.2 | 2.0 | 2.1 | 2.0 | 2.4 | 2.4 | 1.9 | 2.4 | | | |
| **36** | | 1.6 | 2.3 | | | 1.2 | | | | 2.4 | 2.7 | 1.5 | 1.8 | 2.4 | 2.5 | 1.8 | 1.9 | 2.2 | 2.0 | 2.0 | 2.0 | 2.3 | 2.3 | 1.9 | 2.2 | | | |
| **37** | 2.4 | 1.9 | 2.0 | 1.7 | 2.0 | 2.4 | 2.1 | 2.4 | 1.9 | 2.0 | 2.4 | 1.9 | 1.8 | 1.9 | 2.0 | 2.0 | 1.9 | 1.9 | 1.8 | 2.0 | 1.9 | 2.4 | 2.2 | 1.8 | 2.1 | 2.4 | 1.7 | 2.5 |
| **38** | 1.6 | 1.9 | 1.8 | 1.9 | 2.1 | 2.4 | 1.9 | 1.6 | 1.6 | 2.0 | 2.3 | 1.7 | 1.8 | 1.9 | 2.0 | 2.0 | 1.9 | 1.8 | 1.9 | 2.0 | 1.9 | 2.2 | 2.3 | 1.8 | 2.1 | 2.6 | 2.2 | 2.5 |
| **39** | 1.8 | 1.7 | 1.9 | 1.9 | 1.8 | 2.2 | 1.9 | 2.1 | 2.0 | 1.8 | 2.1 | 1.7 | 1.8 | 1.7 | 1.8 | 1.9 | 1.8 | 1.8 | 1.7 | 1.9 | 1.8 | 2.1 | 2.2 | 1.8 | 1.9 | 2.2 | 2.4 | 2.4 |

[1]Service sectors (27-31) are not shown as these values are nan (not a number) since they all have a value of zero in the model outputs (due to lack of records on service sector movements to create shares).

[2]Grey boxes show nan values which means that the average of the commodity flows was zero for these supply chains.

**Table A. 4 2035 Forecast Mean COVs for the Outputs ($t_{jkd}$) of the Third Sub-model Averaged Over ($d$)**

| j,k | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.2 | 0.7 | 0.4 | 0.5 | 0.2 | 0.3 | 1.0 | 0.5 | [1] | 4.3 | 1.3 |
| **2** | 0.2 | 0.2 | 0.4 | 0.4 | 0.2 | 0.7 | 0.8 | 0.5 | | | 0.8 |
| **3** | 0.2 | 0.4 | 0.4 | 0.2 | 0.3 | 0.5 | 2.1 | 1.0 | | | 2.4 |
| **4** | 0.5 | 0.6 | 0.6 | 0.3 | 0.2 | 0.5 | 0.9 | 0.8 | | | |
| **5** | 0.4 | 0.5 | 0.5 | 0.2 | 0.2 | 0.8 | 1.1 | 0.6 | | 4.5 | 1.5 |
| **6** | 0.3 | 1.0 | 0.8 | 0.5 | 0.1 | 0.6 | 0.4 | 0.6 | 1.1 | 3.2 | 1.5 |
| **7** | 0.9 | 0.6 | 0.8 | 1.2 | 0.3 | 0.4 | 1.1 | 0.7 | | | |
| **8** | 2.0 | 1.2 | 0.8 | 1.0 | 0.3 | 0.4 | 0.8 | 0.7 | | | |
| **9** | | | | | | 0.6 | | | 1.7 | | |
| **10** | | | | | | | | | | | |
| **11** | 2.0 | 2.0 | | | 2.1 | | | | | | 2.1 |

[1]Grey boxes show nan values which means that the average of the commodity flows was zero for these supply chains.