Performance Term 3 Forecast and Measurement of Demand Elasticity for British Columbia Ferry Services Inc.

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Table of Contents

1.0 Introduction ... 3
1.1 Forecast is for PT3 traffic by route group ... 3
1.2 Introductory comments regarding the forecast ... 3
1.3 Use of the forecast ... 4
1.4 Forecasts are for the aggregate traffic index required to establish the PT3 price cap ... 4
1.5 A key focus of the forecast is the fare elasticity ... 5
1.6 Organisation of this report ... 6

2.0 Analysis of Quarterly Data on Major Route Group: 2003-2011 ... 8
2.1 Introduction ... 8
2.2 Data ... 8
2.3 Econometric analysis of demand for BCFS services ... 12
2.3.1 Concepts ... 12
2.3.2 Simultaneous Equations Issues ... 13

3.0 Results ... 15
3.1 Introduction ... 15
3.2 Key results ... 15
3.3 The Preferred forecasting model ... 19
3.3.1 Majors ... 19
3.3.2 Route 3 ... 21
3.3.3 North ... 22
3.3.4 Minors ... 23
3.4 Summary of price elasticities ... 23

4.0 Forecast of PT3 Demand for BCFS Services ... 24
4.1 Introduction ... 24
4.2 The stochastic modelling process ... 24
4.3 Forecasts of the exogenous variables ... 25
4.3.1 British Columbia GDP ... 25
4.3.2 Price ... 26
4.4 The risk factors used for the analysis ... 28
4.4.1 Probability Distributions ... 28
4.4.2 Stochastic risk analysis of the BCFS traffic forecasts ... 29
4.5 Forecasting Results ... 32
4.5.1 Majors ... 32
4.5.2 Route 3 ... 36
4.5.4 North ... 39
4.5.5 Minors ... 42

5.0 Cross Price Elasticity: Price Elasticity of Demand Estimation and Net Traffic Stimulus ... 45
5.1 Price elasticity ... 45
5.2 Cross price elasticity ... 45
5.3 Cross price elasticity for BCFS services ... 46
5.4 Regression results ... 47

6.0 Are the Price Elasticity Estimates Sensible? ... 51

6.1 Introduction ... 51
6.2 Key observations on price elasticities for BCFS services ... 51
6.3 A common sense test ... 52
6.4 PT2 forecast and expected traffic impact ... 53

7.0 Key Findings ... 56
7.1 The challenge of forecasting BCFS traffic for PT3 ... 56
7.2 Findings from the regression analysis ... 56
7.3 Findings from the forecast ... 58
7.4 Comments on the econometric estimates ... 59

Appendix A: Definitions and Sources of Data ... 61

Appendix B: Correlations of Traffic Categories for Major Route Group ... 65

Appendix C: A Short Description of Regression Analysis ... 67
Ordinary Least Squares ... 68
Two Stage Least Squares (2SLS) ... 70

Appendix D: Regression Analysis of Route Group “Majors” ... 76

Appendix E: Plots of Historical Traffic Data on Route Groups ... 84

Appendix F: Traffic Forecasts by Route Group ... 88

Appendix G: List of BCFS Routes and Route Groups ... 93

Glossary and List of Abbreviations ... 94

1.0 Introduction

1.1 Forecast is for PT3 traffic by route group

This report develops a forecast for the traffic of British Columbia Ferry Services Inc. (BCFS) for the four years of Performance Term 3 (PT3) and the last year of Performance Term 2 (PT2). The forecast developed in this report is for FY2012 to FY2016:

- PT3 runs from 1 April 2012 to 31 March 2016.
- A forecast is also needed for the last year of PT2, that is for the period form 1 April 2011 to 31 March 2012, i.e., for all of FY2012. (PT2 runs from 1 April 2008 to 31 March 2012.)
- Thus the forecasts in this report cover the five year period from 1 April 2011 to 31 March 2016.
- In developing the forecast we utilise the publicly available historical data from the quarterly monitoring of BCFS relative to its price caps. This will ensure that the forecasted traffic for each route group is fully compatible with the traffic data needed by the British Columbia Ferries Commissioner (the Commission, hereafter) to establish the PT3 price cap. This historic data begins in the April-June 2003 quarter (which is FY2004 Quarter 1),[1] and is available to the quarter ending March 2011 (which is FY2011 Quarter 4).[2]
- While we utilise quarterly data, our focus is on producing forecasts of annual traffic.

1.2 Introductory comments regarding the forecast

It is appropriate to begin this report with a few general statements.

First, there have been some dramatic changes in the 2003-2011 period in traffic drivers, such as severe global recession and high fuel prices, BCFS traffic was largely flat during this period, with a small net decline. It is difficult to uncover meaningful statistical relationships for a forecast model when traffic is flat, especially when driver variables have considerable variation.

Second, our investigation suggests that BCFS traffic may be in the middle of a major transition. In the 1990s there appeared to be stable relationships with key drivers such as population and gasoline prices. Today, however, there are major changes underway. For example, while population may still be a driver of BCFS traffic, demographic changes are also underway. Many residents who had commuted regularly in the past, are reaching retirement age and travelling less frequently and for different purposes. In some areas of the BCFS service territory, there has been an increase in non-resident property ownership, which may also be changing traffic patterns, such as replacing a former commuter with less frequent, leisure oriented travel. Statistically, what our investigation has found is more ambiguous relationships between traditional traffic drivers and actual BCFS traffic, than were found in the past. These findings that are consistent with a

[1] In this document we use fiscal year dates, unless indicated otherwise by use of month name.

[2] This data has been adjusted over the years by BCFS and the Commission for data definitions, the construction of route groups and the transition from PT1 to PT2. These data changes are recognized and accounted for in the econometric analysis in this report.

major change being underway in the demand for BCFS services. This is compounded by the severe effects of past few years of general economic crisis. Despite continuing population growth and recovery from the 2008 crisis, BCFS traffic has largely been flat during the PT2 period and declining on some routes or for some periods of time.

Third, the forecast methodology used in this report reveals that there is considerable uncertainty for BCFS future traffic levels. Some forecast methodologies produce a single "base case" or "central" forecast, and create the illusion that future traffic is reasonably certain. This, of course, is an illusion. There is considerable uncertainty in drivers such as GDP, with the possibility that a recession (or two) could occur between now and 2016. Other factors could act upon BCFS traffic. Some are positive, such as unexpected high tourism growth, but others are negative, such the impact of a terrorism event such as 9/11. Our methodology reveals that while BCFS traffic may grow slightly in PT3, there is almost an equal probability that it will not grow or decline.

1.3 Use of the forecast

Our understanding is that the primary use of the traffic forecast will be in the computing of the price cap which will apply to BCFS in PT3. The price caps, one for each route group,[3] are set separately for each year of PT3. While there are several subtleties to the establishment of the PT3 price caps, it essentially involves dividing the Commission forecasted maximum allowable revenue from fares for a route group by a forecast of the aggregate traffic index for the route group.[4] Hence the need for a forecast of traffic.

1.4 Forecasts are for the aggregate traffic index required to establish the PT3 price cap

The forecasting approaches used in the past were to separately analyse and forecast each of the ten traffic types for each route group, a process that could involve 40 separate forecasts. However, the quarterly computation of the price cap and its corresponding price index requires aggregating the individual traffic component forecasts into a single overall index of traffic.[5,6] Given that the quarterly price cap compliance computations already compute an aggregate traffic index, it seemed sensible to develop a forecast for this index rather than forecast each of the forty individual traffic components. Doing so produces a forecast of the measure required by the Commission to establish the PT3 price cap. Thus, this report forecasts the aggregate traffic index and not the individual traffic components.[7]

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[3] Currently there are four route groups: Majors, Route 3, Minors and North. A list of routes and their assignment to route groups is provided in Appendix G. We understand that in PT3 it is likely that the majors and Route 3 will be combined into a single group. Nevertheless, we conducted our analysis with the historical data (and developed PT3 forecasts) for each of Majors and Route 3.

[4] The *traffic index* can also be referred to as the *quantity index* or the *output index*. In this report, we have tried to utilise the term traffic index. The maximum allowable revenue from fares can roughly be described as anticipated and allowed annual costs of providing ferry services less an allowance for subsidies and net commercial revenues earned in PT2.

[5] In the quarterly price compliance computations this traffic index is referred to as the *dual quantity index* for each route group. This growth in this aggregate index of traffic is essentially a weighted average of the growth in the individual traffic components. While there are some index number computational subtleties, the price cap is roughly the maximum allowed average revenue.

[6] The price index (sometimes referred to as the price compliance index) is the index of the actual average revenue received by BCFS on the route group. The two are compared each quarter to determine whether BCFS is in compliance with its price cap.

[7] If the traffic components are driven by different factors and have different trends, it could be desirable to analyse and forecast each traffic component separately. However, as is discussed later in this report, the different traffic measures are highly

1.5 A key focus of the forecast is the fare elasticity

Traffic forecasts are generally forecasts of the demand for transportation services by the customers of the service provider (BCFS in this case). Demand for transportation services depend on various factors, such as demographic trends, economic conditions and the price of the transportation service. One approach to developing a forecast is to specify and estimate a demand model,[8] and then feed into it forecasts of future demographics, economic activity and the expected future price of the transport service, to produce the forecast of traffic. This however becomes circular, in that the future price of the transport service will depend on the future traffic level, which depends on the future price. Economics refer to this as the *simultaneous equations problem*. Price and traffic are determined simultaneously and thus a complex multi-equation model of the market (both supply and demand) needs to be constructed. If the market is regulated, this can become even more complex.

Most forecast models avoid this by using what economists call *reduced form* equations. These effectively integrate the supply and demand relationships.[9] The reduced form equation for traffic will depend on the forecasts for demographics and economic activity, but it will not require a forecast of price. Essentially, the reduced form approach has coefficients on the variables (other than price) that incorporate their indirect effect on price. E.g., the reduced form coefficient on GDP will based on the effect that GDP has in increasing demand for BCFS services. This generally means that higher GDP will result in higher demand for ferry services, which will drive higher prices for these services, which in turn will result in a lower traffic forecast. A reduced form equation recognises both the direct and indirect effects of GDP on traffic, including this indirect offsetting effect of GDP growth on price. Reduced form equations generally produce good forecasts.

The problem with the reduced form equation approach is that the Commission wishes to explicitly consider the effect of price in its computation of the price cap. Specifically, if the PT3 price cap indicates fares will need to increase above the rate of inflation, the Commission wishes to consider the impact of the higher fare increase on the traffic level, as that may require a re-computation of the price cap. Another way of stating this is that the Commission wishes to make explicit and internalise the effect of price elasticity when it computes the price cap. This means that a reduced form forecasting model cannot be used. Instead, the forecasting methodology will require estimating the demand equation for BCFS services, including an estimate of the price elasticity.[10]

correlated with each other as are their prices. The current revenue shares of the traffic elements are generally within 1% of the shares at the beginning of PT1, hence it was decided that it would not be necessary to forecast each traffic component separately.

[8] The jargon of economists can sometimes be confusing as we use many terms to describe the same concept. A demand model for traffic is essentially an equation (some might say a ‘function’) that relates various quantitative or qualitative factors (or inputs) via a set of coefficients (or parameters) to produce a quantitative forecast (a number) of the demand for transportation services.

[9] The concept is one used in high school algebra, involving substituting one equation into the other. Here, the price (the supply price) determined by the supply equation is substituted into the demand equation for quantity (traffic). The resulting equation for traffic now has all the non-price elements of the demand and supply equations – but it does not have price (it was substituted out of the equation). Such an equation can now be used to forecast traffic. However, if the role of price in the determination of consumer demand for ferry services is of interest or concern, a reduced form equation cannot be used.

[10] A technical econometric note: while the reduced form equation does not directly reveal the price elasticity, it is *sometimes* (not always) possible to infer the price elasticity from the reduced form equation(s). There are actually two reduced form equations: one for quantity and one for traffic. If both are estimated and if a lot of algebra is used, it is sometimes possible to infer the coefficients of the demand and supply structural equations from the coefficients of the price and quantity reduced form equations.

This report meets this need by:

- Estimating a structural demand equation for BCFS services, by route group.[11] We do not use a reduced form approach.
- The structural demand equation for each route group will reveal the price elasticity. This measures the percentage change in traffic when price changes by a given percent.
- When estimating a structural demand equation with price as a variable, one cannot use ordinary least squares (OLS). OLS would produce biased coefficient estimates. Instead, a statistical technique called two stage least squares (2SLS) must be used. This is more complicated and demanding than OLS.[12]
- However, to obtain the traffic forecast with a structural demand equation, it is necessary to have a forecast of the prices BCFS will charge in PT3. We do this by using the draft PT3 price caps contained in the Commission's report of 31 March 2011, adjusted for the announcement by the BC Government that it will establish the price caps by legislation for the first year of PT3.
- We note that if the Commission revises the PT3 price caps, then the forecast will need to be recomputed. However, if the Commission internalises the price elasticity response in its PT3 price cap computation methodology, it should be able to effectively revise the forecast by its internal computations to arrive at the appropriate price cap.

1.6 Organisation of this report

This report is organised as follows:

- Section 2 discusses the methodology and data for estimating the structural demand equation for BCFS service for a route group. This discussion includes both methodology and data issues.
- Section 3 presents the results from the econometric regression analysis using the methodology and data of section 2.
- Section 4 then uses the econometric regression results and produces the PT3 forecast. This section discusses the forecasts of the key variables (e.g., forecasts of GDP) and presents the forecast results. The section ends with a graph and table with the forecast by year for each route group.

Because key elements of the supply of BCFS services are dictated by regulation and the coastal ferry services contract it was decided that the resulting complications made use of the reduced form approach undesirable.

[11] The demand and supply equations in a market are the "structural" equations of how that market works. This is in contrast to the reduced form equation for traffic which nets out the effect of the all the elements of the structural demand and supply equations.

[12] Appendix C discusses the econometric issues of estimating a demand equation and explains why OLS cannot be used and why 2SLS will correctly reveal the price elasticity.

- Section 5 further investigates the issue of price elasticity. BCFS made available two years of daily data on traffic and revenue, as well as a schedule of the days when discounts (CoastSaver fares) were available. This data in not suitable for estimating long run trends for forecasting purposes, as key long run determinants of demand (e.g., BC real GDP and population) are only available annually. However the data does have greater statistical variation on price and traffic than the quarterly data and allows us to see how consumers react day by day to price changes such as discounts. In particular, the section allows us to examine the degree to which increased traffic on days with discounts constitutes increased demand for ferry services, or whether it reflects consumers shifting demand from days with regular fares to days with discounts.

- Section 6 applies a common sense test on our price elasticity estimates. It considers whether higher price elasticities than those we estimate are consistent with the actual traffic experienced by BCFS during PT2.

- Section 7 provides a concise set of key conclusions.

This report includes several appendices:

- Appendix A describes our data and its sources.

- Appendix B provides correlations among the different components of BCFS traffic.

- Appendix C provides a brief background description of regression analysis, including a description as to why OLS cannot be used to estimate a structural demand equation.

- Appendix D gives a detailed discussion of the results of a series of regressions with data on the Major route group. It is provided to demonstrate the approach we used for each of the route groups to investigate and analyse the data and how we accept or reject results for the econometric model of the demand for BCFS services.

- Appendix E provides graphs of the historical data on traffic for each of the route groups.

- Appendix F provides the quarter by quarter details of our forecasts.

- Appendix G contains a list of BCFS routes and their assignment to route groups in PT2.

- Finally, there is a glossary and list of abbreviations.

2.0 Analysis of Quarterly Data on Major Route Group: 2003-2011

2.1 Introduction

This section summarizes data, methodology used, and issues in the econometric analysis of the demand for ferry services. Section 3 will describe our key results of the demand for ferry services, and Section 4 will use those results to forecast the demand for BCFS services in PT3.

2.2 Data

A complete list of data and sources is provided in Appendix A.

The data for the Major route group runs from FY2004 Q1 (the 2nd quarter of calendar year 2003) to FY2011Q4 (the 1st quarter of calendar year 2011).[13] BCFS advised us that earlier data on the aggregate traffic index for each route group is unreliable.

Traffic Measure. It was decided to do the analysis using the overall traffic index from the quarterly price compliance computations rather than do analysis separately for each category of traffic.[14] There are several reasons for confining our analysis to the overall quantity index:

- First, the use of the forecast is for establishing the price cap for PT3.[15] While there are several subtleties to this, it essentially involves dividing the forecast maximum allowable revenue from fares for a route group by a forecast of traffic index for the route group. If traffic is forecast for each of the ten traffic categories, these forecasts will have to be aggregated into a forecast of the overall quantity index for the route group. This in turn requires assumptions on how to construct the traffic index from its components. It also requires forecasts for each of the ten traffic components, and an assumption on how to link the traffic forecast for one category (e.g., adult passengers) to traffic of categories that are not analysed (e.g., assuming child passengers grow at the same rate as adult passengers). Forecasting the traffic index for the route group eliminates all these problems.

- Second, the behaviour of an aggregate index is generally more stable than its individual constituent parts. Thus, analysis of the aggregate index should give the researcher greater confidence in the sense that it is less likely to be the case that econometric analysis will capture a spurious relationship from a chance correlation.

- Third, the key requirement for using an overall traffic index is met by the data. That requirement is that traffic mix is stable. It could be that an overall index remains the same, or is growing steadily while its underlying components are moving in different directions or with different patterns. For example, passenger traffic could be declining while truck traffic is growing, resulting in no change

[13] BCFS operates on a fiscal year ending March 31. Thus the data used in this study runs from FY2004Q1 to FY2011Q4.

[14] This is the dual quantity index computed each quarter as actual revenue for all regulated services on the majors route group, divided by the price compliance index for that quarter. Because of the adjustments made to the price cap index at the end of performance term 1, it is necessary to include a shift variable for performance term 2 (PT2), to ensure that the statistical estimation for PT2 does not incorrectly try to attribute the change in the quantity index due to the adjustment to any of the forecast variables.

[15] Performance terms are the stated periods of regulation, lasting 16 quarters. PT3 begins April 2012 and ends 31 March 2016.

of the overall traffic index. However, analysis of the data for the individual traffic measures for the Major route group shows that:

- The revenue shares of the individual traffic categories have varied only by 1% for each of the categories over the 2003-2011 period. This is a remarkably stable traffic mix, or at least a stable mix of the revenues from different traffic categories.[16]

- The correlations between the traffic categories are very high, indicating that the traffic levels themselves are moving similarly. Appendix B provides these correlations, both for traffic and for the yields of each category.[17] Some key observations are:
  - Correlation is high among measure of passenger traffic of various types. For example, the correlation between adult passengers and seniors is 91%, and with child passengers is 96%.
  - Correlation is relatively high between the measure of adult passengers and the number of passenger vehicles (99%).
  - Correlation between adult passengers and the truck traffic measure is moderately high (65%) and high with buses (91%).
  - Correlation among the yields of different traffic types is even higher than for the traffic measures.
- The conclusion we reach, is that use of analysis on the traffic index, rather than separately analyse (and forecast) each of the ten traffic categories is acceptable.

Variables used in the analysis. First, we indicate a variable we have not used in our analysis:

- Nominal GDP.
  Nominal measures of economic activity (i.e., measures which are not adjusted for inflation) are never used by economists for forecasting traffic. Such measures would dictate that traffic would grow merely due to inflation, a phenomena rejected by economic theory and by common sense.[18]

We now turn to the variable we used in our analysis of BCFS traffic. These include:

- Real GDP.
  This is a variable found in most transportation forecasting models. Higher income is generally expected to increase demand for transportation services, whether freight or passenger.[19]

[16] This can be observed from the quarterly spreadsheets for the price compliance indexes for the Majors route group. See the revenue weights that are computed using the modified Tornqvist methodology.

[17] Yields are computed as total revenue from the traffic category divided by the traffic measure. It is average price paid.

[18] E.g., if the econometric results suggest that traffic grows at 60% of the rate of growth of nominal GDP, then if inflation increases from its current 2% per annum, to 5% per annum, then BCFS traffic would be expected to grow by 1.8%, even if BCFS increases its prices by the rate of inflation.

[19] There is a hypothetical exception. If a transportation service is considered to be an inferior service relative to other available transportation services, then if GDP grows, consumers will substitute to the more desirable transportation services. This has been offered (by some) as a reason why post world war II use of urban bus services declined – as incomes grew (income is highly correlated with GDP), individuals migrated from mass transit to autos for commuting and other trips.

- Population.
  We measure population on a per capita basis, not the number of households. The latter generally grows faster than population as average family size declines, and the most important usages of ferry services are population based, not household based.

- Trend.
  In addition to growth in traffic due to growth in economic activity or population, some transportation services have further growth (or declines). E.g., research conducted by Inter*VISTAS* for the aviation sector revealed that there are both life cycle and life style factors which have been driving an increase in the demand for air transportation, over and above growth driven by the ups and downs of GDP or population. We investigate whether any trend is apparent for the demand for BCFS services.

- Price of gasoline for automobile use.
  Economic theory would suggest that if the price of gasoline increases, auto travel will decrease, and hence ferry travel would also decrease.

- Price of Marine Diesel.
  While the prices of marine diesel and gasoline are very strongly correlated, we recognise that these are two different variables.
    - The price of gasoline drives the *demand* for auto trips, hence ferry services. It is the correct demand equation variable to use.
    - The price of marine diesel affects that cost of operating ferry services, hence it is the correct supply equation variable to use.

There are also variables which should be introduced in econometric analysis to indicate when the demand or supply relationships shifted, usually temporarily. There are separate shift variables for demand factors and supply factors. The correct term for these variables is demand (or supply) shift indicator variable, but unfortunately, it has become common for researchers to refer to these as "dummy" variables. A few examples:

- If there is a work stoppage due to a labour action, then the supply of ferry services in a given quarter is reduced. It is important to 'control for' this effect by use of an appropriate indicator variable, as otherwise the statistical/econometric methodology will incorrectly attempt to attribute the drop in traffic for that quarter to some other variable, or it will incorrectly determine that the other variables have weaker impacts of ferry traffic.

- If there is an event which temporarily increases ferry traffic, then an appropriate indicator shift variable is required. Examples might include the effect of a special event such as the Olympics, or a temporary increase in ferry demand if mainland-island air services are interrupted for a considerable number of weeks (e.g., due to bankruptcy of a carrier).

For our analysis of BCFS routes, we considered the following indicator variables:

Supply factors:

- Work stoppages due to labour disruptions.

- Loss of capacity due to the loss of the Queen of the North (only affects North route group).

Demand factors:

- 2010 Olympics.
- SARS.

Data redefinitions:

- In addition, over the years there have been two data redefinitions, which cause the data series (both traffic and price) to shift at a particular point in time. These shifts need to be controlled for; otherwise the regression analysis will incorrectly try to attribute the shift in the data measure to an explanatory variable, resulting in bias in the coefficient results. These are described shortly.

Price.

Our analysis utilised as the price of ferry services for purposes of analysing demand for ferry services, as the "all-in price". This is the price actually paid by ferry passengers, and is not necessarily what is received by BCFS from users of its services. Key elements include:

- The all-in price includes fuel surcharges paid and/or rebates received.
  The accounting treatment might assign some fuel surcharge revenues to the fuel surcharge account established by the Commission, rather than to BCFS quarterly revenues. We measured price as what the passenger actually paid in a given quarter, regardless of the accounting treatment of the revenues.

- The all-in price is net of CoastSaver discounts.

- The all-in price is net of contributions from the provincial government for transportation of seniors or other social programs. For analysing the demand for ferry services, we only utilise the amount actually paid by seniors or other social program recipients.

Supply variables.

First, a bit of economic theory. The supply equation for a firm or a market indicates how the quantity supplied varies with price. In a non-regulated market, if market price increases due to higher demand, more supply will generally be forthcoming, either because existing suppliers find it profitable to add capacity, or because new suppliers are attracted to enter the market.

Alternatively, and perhaps more intuitively, the supply equation relates the price that is needed for a given level of capacity to be supplied. For example, if the firm's costs go up, it will require a higher price in order to supply a given level of capacity. Thus, when estimating the supply relationship in the market for ferry service, the supply equation includes not only the quantity of services provided by the firm, but also the price it receives for the service, the costs it must incur to provide the services, and other variables.

Normally, the price a firm receives for its services and the level of traffic it serves are 'endogenous" variables. That is, the price and level of traffic are jointly (or simultaneously) determined by consumer demand and conditions of supply (e.g., the costs to provide services).

There are also "exogenous" variables that affect supply price or supply quantity. These are factors that are NOT jointly determined with consumer demand. For BCFS these include:

- The cost of its inputs.
    - Often, this would be modeled by including the price the firm pays for labour services, the price it pays for capital, the price it pays for fuel, etc.
    - However, a commonly used alternative is to compute a single overall index of all these input prices. This was done in earlier work by BCFS to measure the total factor productivity of its operations.[20] An "aggregate input price index" was computed from a weighted average of the growth in the individual prices of labour, capital, fuel and other purchased services and materials.[21] An input price index can also be constructed by dividing the firm's total costs by its traffic index.[22]
    - For BCFS, however, there is another input price index. That is the price cap index. The price cap index, which is determined by the Commission, divides the net costs incurred by BCFS by its quantity index.[23,24]

Accordingly, our econometric analysis used the price cap index as the aggregate measure of BCFS input prices.[25]

Our analysis also included previously described indicator variables for capacity lost due to work stoppages or due to the loss of the Queen of the North.

2.3 Econometric analysis of demand for BCFS services

2.3.1 Concepts

Given that capacity is largely set by the Coastal Ferry Services Contract between the Province and BCFS, the exercise of forecasting traffic for BCFS is one of forecasting demand.[26] This is common in the transport industry.

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[20] The last version of the TFP results are for early 2009.

[21] This methodology is the same as the computation of the price compliance index using the Tornqvist methodology.

[22] Technically, this is a dual input price index. It is dual to the traffic index.

[23] The establishment of the price cap for BCFS services involves estimation of the costs that will be incurred to by BCFS to provide services, and then offsetting this by net revenues from non-regulated services (such as on board retail and food services, parking and reservations).

[24] There are a few subtleties here, however. The price cap index is a projected input price index. It is based on dividing the projected BCFS net costs by the projected traffic index. Nonetheless, it is an input price index and the one which guides BCFS decisions. There is also the issue of fuel price. The Price Cap index embodies a "set price" for fuel. Actual fuel cost may be higher or lower.

[25] We supplemented the price cap index with the percent of BCFS costs accounted for by higher (or lower) fuel prices relative to the set price.

[26] The contract between BCFS and the Province specifies which routes are to be operated, the number of sailings, and the capacity of vessels. Safety regulations determine the required staffing of vessel services. Thus, almost all dimensions of supply of capacity are determined by the contract.

For example, airport forecasts are forecasts of demand for airport services (movements of aircraft) and airline services (number of passengers and number of tonnes of cargo). As airport revenues are driven by both movements and passengers/cargo tonnes, airports typically forecast both movement and airline traffic. If an airport is congested, meaning demand exceeds available capacity, then a two-step process is used. First, unconstrained demand is forecast, typically with an econometric model with a stochastic simulation to obtain the range of traffic outcomes. Second, capacity is considered and if demand exceeds capacity in a fundamental way, then a constrained forecast is produced which recognises that some airport demand will not be served.[27]

This is also similar to forecasting demand for urban transportation. Because of the complexity of the urban transportation network, these models are very complex. But they involve forecasting demand for trips between regions of the urban area, then recognizing the constraints in the road and transit network and allocating the demand to different routes or times.

For BCFS, our understanding is that with the exception of a few peak periods during the year, on most routes capacity exceeds demand, hence a complex forecast process is not required. Our approach is to forecast demand for ferry services by its customers. We do not attenuate demand by capacity constraints as most BCFS services are not capacity constrained.[28]

This approach means that we can estimate a demand equation, and then forecast demand using forecasts of key exogenous demand variables (such as GDP, population, etc.).[29]

2.3.2 Simultaneous Equations Issues

To estimate the key parameters of the demand for BCFS services, we utilise statistical regression analysis. This is a common practice for forecasting. The use of statistical methodologies (such as regression analysis) when analysing economic relationships is often referred to as econometric analysis.[30]

For those unfamiliar with regression analysis, Appendix C provides a short description of statistical regression techniques.

- It begins by describing ordinary least squares (OLS) regression.

- It then discusses the challenges of estimating a traffic demand equation. Because traffic and price are determined simultaneously by the interaction of supply and demand in a market, it turns out

[27] As an example, at a busy airport such as Washington Reagan, there is a limit on aircraft movements, so some demand for service at Reagan will be unmet, either by the traffic having to use another airport (e.g., Washington Dulles or Baltimore-Washington), or demand will simply be unmet. (E.g., it is widely believed that a significant amount of demand for service to London UK is unmet).

[28] On the busy Majors routes, individual sailings may fill to capacity but demand generally shifts to the next available sailing, or consumers make reservation in advance to obtain service on their preferred sailing.

[29] We do not need to forecast the exogenous supply variables, although we need historical data on these variables in order to estimate the demand equation using 2SLS.

[30] Econometrics differs from mere statistical analysis in that it requires estimated relationships to be consistent with economic theory. Blind statistics analysis, for example, might estimate a forecasting equation which indicates higher fares result in more passenger traffic. Econometric analysis recognises that higher prices should result in lower traffic, and thus would reject such a finding, even if measures such as the statistical “goodness of fit” are high. Perhaps another way of expressing this is that econometric analysis applies economics common sense before accepting any finding.

that OLS cannot be used to estimate the coefficients of a demand equation. OLS will produce biased estimates of the parameters of a demand forecasting equation, potentially seriously biased estimates.

- While OLS is unacceptable, there is an econometric regression methodology that can produce unbiased estimates of a traffic demand model. This is called two stage least squares (2SLS), and it is also described in Appendix C.

Because a BCFS demand forecast model cannot be estimated using ordinary least squares, as this would result in potentially severe bias in the statistical estimates, we have decided to estimate the demand for BCFS services equation using best practices, that is, using 2SLS.

3.0 Results

3.1 Introduction

This section discusses the results of our statistical estimation of the forecasting equations for the demand for BCFS services. The section provides the key findings for the various variables affecting the demand for services, and provides the final forecasting equations we adopt.

To illustrate the approach we used to the econometric analysis, Appendix D describes our econometric results in detail for the Major route group. It provides tables of a number of regressions for the Major route group. The appendix starts with the simplest regression and gradually builds greater complexity. While eventually we will choose a preferred regression to be used for forecasting, this approach of building to the preferred regression is desirable, as it typically reveals whether the regression results are stable and robust, and whether there are any variables which produce unrealistic results (e.g., population growth reducing the demand for ferry services). Our approach starts with simple regressions, estimated with OLS if price is not in the regression, and builds toward more complex regressions, estimated using 2SLS when price is in the equation.

Similar analysis was conducted for the other three route groups but for brevity we describe the detail of our approach for only one route group, the Majors.

3.2 Key results

Key results of the econometric estimation are as follows:

Seasonality

- The quarter by quarter demand for BCFS services is strongly seasonal.
    - Simply controlling for (i.e., simply introducing variables for) the different quarters explains 99% of the variation in the quarterly data.[31]

- In Section 5 we do some additional analysis using daily data to investigate the degree to which lower prices for some sailing (e.g., CoastSaver fares) stimulates new traffic demand, or largely shifts demand from a sailing at the regular price to a sailing at a discounted price.
    - Controlling only for months of year with the daily data explains 64% of the variation in daily traffic data.
    - Controlling only for days of the week explains 39% of the variation in the daily data.
    - Controlling for both day of week and month of the year explains 80% of the variation in the data.

- Thus, regression models with high R^2 can be achieved with the BCFS data merely by controlling for quarter/month and day of week. This underscores a main point in forecasting analysis: a high R^2 does not mean that the model is explaining any economic phenomena, such as the relationship of traffic with price or GDP or population. We must look beyond the R^2 measure when choosing

[31] The percent of variation in the data that is explained by the regression equation is the R^2, a measure of the goodness of fit of the regression.

the preferred regression model.

- Other key variables that are statistically significant with the daily data are those indicating whether a given day is a holiday; or 1 day, 2 days, or 3 days before/after a holiday. Adding these holiday indicators increases the R^2 to 87%.

Demand Shift Variables

- For Northern routes, the demand shift when the capacity of the Queen of the North was unavailable is statistically significant. It indicates that traffic on the Northern routes fell by roughly 15% during these quarters.

- The demand shift due to a 2004 work stoppage is not always statistically significant in all the regressions, but is included in our analysis as it is a known factor.

- Similarly the demand shift for the Olympics is included, even though the effect is not always statistically significant.

Data Redefinition

- BCFS redefined some of its data at the end of 2005, and a shift variable is included in all models to denote the earlier data before the redefinition.

- Similarly, a shift is included beginning in PT2,[32] as the Commission redefined some elements in both the price and quantity indexes at the end of PT1.

- Although these variables do not always have statistically significant results, they are included in all models as the effects are known to be present in the data.

Trend

- Results for a trend variable are sometimes positive and sometimes negative and statistically insignificant. A trend variable does not appear to be significant, and if a trend is present, it is most likely to be negative.

- In the quarterly data, a regression only on trend (with a constant, of course) suggests that ferry traffic has no trend.

Population and demographics

- We were generally unable to obtain meaningful regressions containing a population variable. Sign was more often than not incorrect (i.e., implying population growth reduces ferry traffic). Magnitudes of the population effect were variable and generally implausible. This is true whether we used simple ordinary least squares or 2SLS.

[32] PT2 began in April 2008 and ends March 2012.

- E.g., simply regressing traffic for the Majors on population produced a negative relationship: a 10% increase in population would decrease BCFS traffic by 0.3%. This result is statistically insignificant.

- While there were a few regressions which had a positive relationship between population and traffic, other results in the model were implausible. We concluded that we could find no meaningful and robust relationship between population and BCFS traffic. Earlier studies of BCFS traffic suggested that in previous decades there was a population to traffic relationship. The current data does not reveal such a relationship. In the past decade, population has grown, while overall BCFS traffic has increased. It may be that the combined effects of recession and higher prices are disguising a traffic to population relationship, but our analysis which tried to include population and economic activity (measured by GDP) still did not reveal any sensible population to traffic relationship. This was true for all four route groups. In spite of attempting several different model specifications we could obtain no meaningful result that linked demographic change to the demand for ferry services. We thus excluded population from our preferred regressions for forecasting traffic to 2016. We would encourage future forecasting studies to re-examine the relationship.

- We note that BCFS has conducted some analysis of demographic shifts on traffic, focusing particularly on the Minor route group. Some of these routes have experienced two phenomena.
  - First, there is an increasing portion of non-resident home ownership, which typically results in lower total annual ferry use vis a vis a resident who commutes daily by ferry.
  - Second, an aging resident population results in lower ferry use when retirement begins. While seniors travel on fares subsidized by the provincial government, travel is less frequent than daily commuting and there may be an overall reduction in ferry traffic. BCFS analysis has found that seniors travel on the Minor route group has increased from 258,000 in FY2004Q3 to 309,000 in FY2011Q3, and now accounts for 6.9% of all passenger traffic (up from 5.5%).

- We note that data from the 1990s and earlier part of the 2000s did reveal traffic-population relationships, but since the mid 2000s, this is no longer the case. We hypothesise that the demand for ferry services is currently in the midst of some changing relationships, as populations age. As well, it is well known that highway based tourism travel from the US has yet to recover to pre 2000 levels. It is not surprising that statistical relationships are weak during a regime change in a market.

Adding GDP

- A regression of traffic on a constant and the Real GDP variable produces a positive relationship, with 10% GDP growth increasing ferry traffic by 3%.

- This finding was maintained through a range of specifications and GDP is in all of our preferred forecasting regressions.

The price of gasoline

- Economic theory and common sense would suggest that higher gasoline prices would decrease the demand for ferry services. As higher gas prices generally reduce highway travel one would expect this effect to reduce the demand for ferry services.

- The regression analysis was unable to find a consistent effect linking ferry traffic to gasoline prices during the period from 2003 to early 2011.

- This was a surprising result, so we investigated a wide range of possible models as well as simple correlation analysis. We found that there were a few cases where higher gasoline prices were correlated with lower ferry traffic, e.g., when comparing year over year October to December quarterly traffic. However, the relationship did not hold for other year over year comparison.

- The ambiguous (non-robust) statistical results may be due to a number of challenges with the data.
    - There is a limited number of data points.
    - In those data points that are available, changes in gasoline prices were occurring simultaneously with changing real GDP, potentially obscuring the effect.
    - However, the data has gasoline prices variously moving with GDP and against GDP, and one would expect that if traffic is responding significantly to gas prices it would have been picked by the regression as an effect separate from the GDP effect. This appears not to be the case in the data.
    - It may be that when gas prices dropped precipitously beginning in July 2008, (from which we might expect ferry traffic to be stimulated), the severity of the 2008 recession and the market psychology of the first truly global recession since the 1930s overwhelmed any positive effect of the fall in gasoline prices.
    - The variation in the data simply does not create a meaningful linkage with gas prices in the regression models we investigated.
    - We were able to observe some evidence of the effect of gasoline price increases decreasing traffic (or price decreases increasing traffic), but the evidence was not consistent. For example, analysis with year over year fourth quarter traffic and gasoline prices reveals the expect effect, but this is not the case with 3rd quarter data.
    - It is likely that the turmoil in our economy since 2007 (oscillating gas prices with a severe recession and subsequent recovery) is such that the gasoline-ferry traffic relationship does not meet the standard of a robust statistical relationship, at least for the present.

- It is our opinion it is highly likely that there is a long term relationship between gasoline prices and demand for ferry services. However, the statistical regression analysis of the post 2003 data simply is not able to reveal such a relationship at this time. We decided to err on the side of caution, and rather than base our preferred forecasting regression on a few cases where we could find the expected relationship and ignore the other cases, we chose to exclude the gasoline price from the preferred regression.

- We expect that repeating the regression analysis in another year or two will provide more data points from which any actual gasoline price impact on ferry demand can be revealed.

Synopsis thus far

The above results are from regressions without price as an explanatory variable. However, the results suggest a few key findings:

- Ferry traffic in the past decade appears to be unlinked to population growth.
- Ferry traffic appears to have no trend.

- Ferry traffic does have a relationship with GDP.
- Seasonality of the overall traffic index is large and dominates the effect of any other variable.

Adding Price

We now examine regressions which include the price of ferry services. As discussed earlier, a model which merely adds price of ferry services to an ordinary least squares regression will be biased. Price can only be included in a regression to determine the coefficients of ferry demand by using the 2SLS econometric technique. We undertook such regressions.

- Regressing ferry demand on the all-in quarterly price index of ferry services (along with regression indicator variables for seasonality etc.) produces an expected result. A 10% decrease in the average price of ferry services increases ferry demand by 1.8%. This result is not statistically significant, but it is consistent with economic theory.

- Adding GDP to a regression with price, changes the price elasticity only slightly, and produces a slightly higher GDP response (10% GDP growth increases traffic demand by 4%).

3.3 The Preferred forecasting model

This subsection presents our preferred regression model for each of the four route groups.

3.3.1 Majors

Appendix D provided a plot of the historical quarterly data for the Major route group. Two plots are provided: one for the actual quarterly index of overall traffic, and one which smooths the data by taking a four quarter trailing average of traffic. This smoothing process removes the quarter by quarter seasonality and allows general trends in traffic to be seen.

Based on the results described above (and the detailed regressions in Appendix D), we conclude for the Majors:

- Ferry demand depends on the price of ferry services, with a price elasticity of roughly -0.28.
- Ferry demand depends on GDP growth (or reduction) with an elasticity of roughly +0.21.
- No discernable impact of population on ferry demand is apparent, at least with this data set.
- The seasonality effect in the total ferry traffic is strong and significant. It dominates the model. Seasonality alone explains 99% of the variation in the quarterly data.
- The effect on the *measure* of ferry traffic from the adjustments to the traffic index at the end of PT1 increased the traffic measure by 6.5%.[33] This shift must be carried forward to the forecasts for PT3.
- The effect of the 2010 Olympics was positive, but small and not statistically significant.
- There was a noticeable and significant reduction in ferry demand during a quarter with a work stoppage, with traffic declining at 8% after controlling for other factors (such as seasonality).

The preferred forecast model, with coefficients and standard errors is as follows:

[33] PT1 began April 2004 and ended 31 March 2008.

Variable	Coefficient	Standard Error
Constant	12.169	2.017
Price Index	-0.279	.131
Real GDP	0.207	.339
Shift from PT1 to PT2	0.065	.026
Data redefinition	-0.004	.017
Seasonal Effect Q1[34]	0.321	.012
Seasonal Effect Q2	0.606	.016
Seasonal Effect Q3	0.148	.014
Olympics impact	.020	.025
Work stoppage impact	-.080	.023

R-square = 0.998

Before moving on to the other route groups, we make a few observations on the statistical significance of some of the estimated coefficients. Some coefficients have strong statistical significance, in that the standard error of the coefficients is much less than the coefficient estimate. Coefficients with good statistical significance include the seasonal effects, price, the effect of a work stoppage and the shift in data definition from PT1 to PT2. Coefficients with weak statistical significance include GDP, the data redefinition which took place (which was a known, but small effect), and effect of the Olympics on ferry traffic.

Some researchers prefer to only include variables in a final regression model whose coefficients are statistically significant. Applied econometricians building forecasting models, however, often will use a model where important variables have the expected sign and magnitude, even if the statistical significance is moderate. The key is whether the coefficient estimate is robust, in the sense that the estimate does not vary with small changes to the regression model or the time period of the data. For example, if a series of regression specifications and data time periods produces coefficient estimates of the right sign and roughly similar magnitude, then the estimate might be considered robust, even if the statistical significance is moderate. For forecasting purposes, it is generally preferred to include such a variable rather than ignore the effect. In our model of ferry demand for the Majors, the GDP coefficient of 0.207 is of moderate statistical significance. However, over a range of models and data time periods, we found that the GDP coefficient estimate was consistently of the correct sign (positive, higher GDP increases ferry traffic and recession reduces it), and the magnitude for this route group was generally in a range of 0.10 to 0.40. Our decision is that it was better to include our estimate of the GDP coefficient for producing PT3 forecasts, than to exclude the GDP variable. This is common practice among forecast model builders.

[34] Seasonal effects are for fiscal year quarters and are relative to the last quarter of the fiscal year.

3.3.2 Route 3

Appendix E provides plots of the historical data for this route group. The preferred regression is as follows:

Variable	Coefficient	Standard Error
Constant	5.728	1.119
Price Index	-0.284	.094
Real GDP	0.754	.144
Shift from PT1 to PT2	0.084	0.017
Data redefinition		
Seasonal Effect Q1[35]	0.004	0.005
Seasonal Effect Q2	0.008	0.006
Seasonal Effect Q3	0.004	0.005
Olympics impact	0.026	0.010

R-square = 0.91

A few comments are in order. First, while we used quarterly traffic for the forecast model for the other routes groups, the Route 3 data (this is the only route group that has only a single route, and the traffic on this route is moderate) did not provide any sensible regression results. Instead, we utilised data that were computed as four quarter trailing averages, which effectively eliminates most seasonality. This data was able to produce the results in the above table, which are sensible. I.e., the price elasticity is negative and the GDP elasticity is positive. Both are of reasonable magnitude (e.g., we would not expect a GDP elasticity of 10). The price elasticity is similar to that of the Majors, although the analysis produces a higher GDP elasticity for Route 3. We also found that inclusion of the data redefinition indictor variable consistently produced nonsensical results. We found that if we excluded this variable, we obtained plausible results.

[35] Seasonal effects are for fiscal year quarters and are relative to the last quarter of the fiscal year.

3.3.3 North

Appendix E provides plots of the historical data for this route group. Note that traffic on this route group has been declining. The preferred regression is as follows:

Variable	Coefficient	Standard Error
Constant	-4.498	5.723
Price Index	-0.562	.316
Real GDP	1.547	.601
Shift from PT1 to PT2	0.131	.031
Data redefinition	0.199	.057
Seasonal Effect Q1[36]	0.966	.112
Seasonal Effect Q2	1.799	.143
Seasonal Effect Q3	0.142	.031
Olympics impact		
Work stoppage impact		
Queen of the North impact	-0.150	0.037

R-square = .997

The estimates for the North differ considerably from those for the Majors and Route 3. This route group appears to be more price elastic than the Southern routes. This is perhaps not surprising as many of the voyages on this route group are longer and of higher price than the Southern routes. Economists often expect that consumers are more price elastic at higher prices. This route group also appears to be much more sensitive to the effect of GDP. We observe that the GDP effect for the North route group was high, often greater than unity, even for other regression model specifications. We were unable to obtain sensible coefficient estimates for the effect of the Olympics (perhaps not surprising for the North routes) or the effect of the work stoppage. The work stoppage was in a quarter with relatively low traffic, and perhaps this was a factor.

It is useful to make a general observation about forecasting traffic for the North route group. This is the route group with the lowest traffic level. Low levels of traffic are always problematic for forecasters as there typically is greater variation from year to year whereas higher traffic levels tend to smooth out variations in demand. As well, while all of the route groups have seasonality and diversity in their customers and trip purposes, the North routes are highly seasonal, with many having a large share of tourism travel which may be unrelated to economic activity in BC or population trends. Some of these routes are long with correspondingly higher cost and fare bases, yet there are also shorter haul trips by residents. We investigated many possible alternative specifications for the forecasting model and regressions and found

[36] Seasonal effects are for fiscal year quarters and are relative to the last quarter of the fiscal year.

this route group to be especially problematic to find a robust forecasting model. We are not the only researchers to have made this observation about modelling and forecasting traffic on North route group.

3.3.4 Minors

Appendix E provides plots of the historical data for this route group. The preferred regression is as follows:

Variable	Coefficient	Standard Error
Constant	11.497	1.697
Price Index	-0.122	.052
Real GDP	0.048	.162
Shift from PT1 to PT2	0.112	.015
Data redefinition	0.003	.015
Seasonal Effect Q1[37]	0.262	.008
Seasonal Effect Q2	0.476	.012
Seasonal Effect Q3	0.079	.009
Olympics impact	0.007	.017
Work stoppage impact	-0.059	.020

R-square = 1.00

For this route group, we found a much lower GDP elasticity than other groups. This is troubling to us, but we found no regression model that produced a higher elasticity. We do observe that the standard error is large relative to the estimated elasticity, so that a somewhat higher GDP elasticity would not be statistically rejected.

3.4 Summary of price elasticities

The following table summarizes the price elasticities by route group. These are relatively modest price elasticities. The issue of the reasonableness of the price elasticities will be discussed further in Sections 6.

Majors	-0.28
Route 3	-0.28
North	-0.56
Minors	-0.12

[37] Seasonal effects are for fiscal year quarters and are relative to the last quarter of the fiscal year.

4.0 Forecast of PT3 Demand for BCFS Services

4.1 Introduction

A Stochastic Risk Adjusted forecasting methodology was used to generate the forecasts of BCFS traffic.

A stochastic forecast is based on the recognition that the future is uncertain, and any one of a number of possible scenarios may be realised. This approach uses a probability based process to generate thousands of potential scenarios and then takes an average across all of them. Each scenario is estimated by randomly generating values for a wide range of factors affecting ferry traffic, based on probability distributions determined by the project team.

The stochastic forecasting approach makes use of the econometric analysis described in the previous section, but also builds in probability profiles of the main factors affecting traffic.

We present the following forecasting results below:

- The 50^{th} percentile forecast. This is an average of the forecast results for 10,000 randomly generated scenarios for each year to 2016.

- The 25/75% forecast range. This is the range of traffic forecasts which account for the central 50% of the forecast scenario outcomes. E.g., below the 25% lower bound 25/75 forecast range, there are possible outcomes, but collectively they represent less than a 25% chance of occurrence.

- The 10/90% forecast range.

- The 5/95% forecast range. There is a chance that BCFS could realise even lower traffic levels, but the chance of occurrence is less than 5%, and would depend on a simultaneous combination of traffic reducing effects.

4.2 The stochastic modelling process

As with any projection of future activity, the forecasts for BCFS are subject to a degree of risk and uncertainty. The forecasts are based on underlying assumptions regarding economic growth and other factors, which are developed from the best available intelligence and analysis. However, it is not possible to determine how these factors might vary over time and when certain events may occur; e.g., the timing of recessions. Furthermore, one-off events may have an impact on traffic but are impossible to predict, such as terrorist attacks or other disasters.

The traditional approach to this issue in traffic forecasting is to supplement the base case forecasts with high and low case forecasts. This conveys that there is uncertainty in the forecast, and provides a rough range for likely outcomes. However, the low case should not be interpreted as a “worst” case, but rather a conceivable though low probability outcome. The low scenario typically embodies slower growth in ferry traffic over the medium to long term due to the combined effect of a slower economy, high fuel prices, etc.

An approach to better understanding the range of possible future scenarios is to apply quantitative risk analysis to the forecast. This approach recognizes that there are a number of key drivers of the forecast (e.g., economy, fares, fuel prices, one-off events, etc.) and that each of these drivers has its own level of uncertainty or its own *probability distribution.* This type of risk analysis utilizes the probabilities around economic performance, fuel costs, etc. to create a large number of potential scenarios. One scenario might be normal economic performance but with high fuel costs. Another might be weak economic performance and high fuel costs but with no pandemic or terrorist event.

Typically, the risk analysis will create thousands of such scenarios, each time randomly generating values for each of the forecast drivers, subject to the probability distribution applied to them. This is often referred to as Monte Carlo simulation. In such analysis, there is undoubtedly a few cases where all forecast drivers have dismal outcomes (poor economy, high fuel cost, a terrorist event, etc.), but most of the "simulations" will have a few drivers low and others high. A few scenarios will even have most of the drivers taking on high values. By considering the results of the thousands of potential scenarios which are simulated by the Monte Carlo process, a probability distribution for the overall forecast can be developed. While the traditional low-case forecast does not postulate a worst case, the risk analysis will show the worst (and best) cases, although the probabilities of these will be small. More probable are scenarios where a few key factors are weak, a few are high and most are close to long term expectations.

From the Monte Carlo analysis a single forecast can be produced by taking an average across all the simulations. This represents the **50th Percentile** forecast given the range of possible future outcomes. However, the real power of the Monte Carlo simulation lies in its ability to provide more meaningful statements regarding this range of possible forecast outcomes. Rather than produce just a single static outcome, the risk analysis process can also provide a probability-weighted range of traffic outcomes, and allow questions to be addressed, such as:

- What is the probability that passenger traffic growth will be flat or less than traffic today?
- What is the probability that passenger traffic will be greater than 3 million in 2016?
- What is the probability that passenger traffic in 2016 will be less than 2.2 million?

4.3 Forecasts of the exogenous variables

In order to generate the forecast of the demand for ferry services in PT3, it was necessary to obtain projections of the two main variables included in the econometric analysis, real GDP and price of ferry services. Each variable requires a forecast for each year of PT3.

4.3.1 British Columbia GDP

For provincial GDP, projections were obtained from major government and commercial forecasters, and an average taken, as illustrated below:

Year (Calendar)	RBC[1]	TD Bank[2]	BMO[3]	Scotiabank[4]	BC Ministry of Finance[5]	Average
2008	n/a	0.2%	0.2%	n/a	0.0.%	
2009	-1.8%	-1.8%	-1.8%	n/a	-2.3%	
2010	3.4%	3.6%	3.8%	3.1%	3.1%	
2011	2.9%	2.6%	3.4%	3.1%	2.2%	2.8%
2012	3.2%	2.3%	3.0%	2.6%	2.8%	2.8%
2013					2.8%	2.8%
2014					2.9%	2.9%
2015						2.8%
2016						2.7%

1. RBC Economics Research: Provincial Outlook, March 2011

2. TD Economics: Provincial Forecast Table, March 2011

3. BMO Capital Markets Economics: Provincial Economic Outlook, April 15, 2011

4. Scotiabank Group Global Economic Research: Global Forecast Update, April 1, 2011

5. BC Ministry of Finance First Quarterly Report 2010/2011

6. CIBC World Markets Inc.: Economic Insights, March 31, 2011

4.3.2 Price

Demand for ferry services depends on the price that will be charged. Thus a demand forecast of traffic requires a forecast of future ferry prices.

In non-regulated markets, this can be done by estimating a supply equation as well as a demand equation and then solving them (supply must equal demand) for each year. Alternatively, one can estimate a *reduced form* model of the market. This results in an equation for traffic which does not have price, but which contains all the other supply and demand variables. Essentially this reduced form equation provides a solution for each year of equating supply and demand.

There are problems with using either approach. First, BCFS is a regulated firm. Its price is not the outcome of a normal market process. Rather, the Commission examines cost and other factors and sets a cap on the prices that BCFS can charge. This rules out use of the normal forecasting procedure.

As well, the reduced form approach cannot be used, as in setting the price cap for PT3 the Commission wishes to recognize the elasticity response in the market.

- Roughly speaking, the Commission determines allowed BCFS costs for each route group and provides some offsets to these (e.g., BCFS costs are offset by past net earnings from non-regulated services such as food/beverage/retail).

- These allowed costs are then divided by the traffic forecast to determine the price cap for each year.

- However, higher prices for ferry services will result in some reduction in the demand for services. Thus, the traffic forecast will change, which in turn will change the price cap for PT3.

- To address this mutual dependence, the Commission requires an estimate of the fare elasticity, so that the computation of the price cap can factor in the elasticity response.

- Thus, the forecasting model must provide an estimate of the fare elasticity.

This poses a problem for this study. Our objective is to produce a traffic forecast. However, that forecast will depend on the price cap to be set by the Commission for PT3. What we have done for the traffic forecast presented below is to use the preliminary price cap set by the Commission on 31 March 2011. If the final price caps change, then the forecasts will change as well. However the price elasticity in this report will allow the Commission to make the needed adjustments.

The Commission's preliminary projections for the price cap for PT3 are

- 4.15% annual growth on the Major and Route 3 route groups, and

- 8.23% per annum on the North and Minor route groups.[38]

On 25 May 2011, the Province introduced legislation which would set the price cap for the Minor and North route groups at 4.15% for the first year of PT3. Thus our price forecast for these two route groups utilise 4.15% for Year 1 of PT3 and 8.23% for the other years.[39]

We also observe that as a result of the duty remission with respect to importation of foreign-built vessels announced by the Federal Government in October 2010, the Province and BCFS entered into an agreement whereby BCFS would lower fares by 2.0% on Route 3, the Minors, and the North in lieu of the provincial government implementing a previously scheduled reduction in the payment under the Coastal Ferry Services Contract.[40]

[38] The forecast period covered the period April 2011-March 2012 which is covered by the PT2 price cap. For this period, the price growth was based on the existing price caps:
Majors: 2.5% per annum + 0.49 CPI growth (where CPI growth was assumed to be 2.5% per annum);
Other: 5.7% per annum + 0.73 CPI growth (where CPI growth was assumed to be 2.5% per annum).

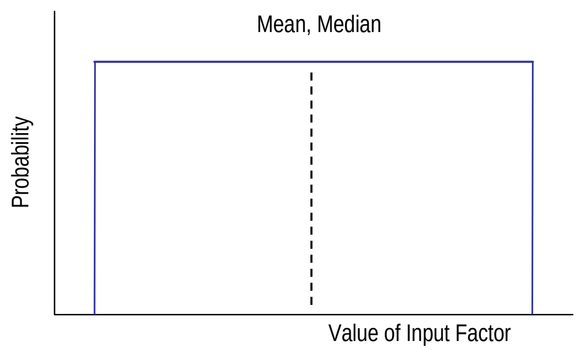
[39] We note that BCFS will not necessarily increase its prices by the same amount allowed by the price cap. We observe that BCFS is currently below its price cap at present, and thus is entitled to increase its fares by more than the 2012 price cap, so as to catch up with the price cap allowed previous. Further, at this point we do not know exactly what will happen with fuel surcharges relative to the fuel 'set price' for PT2 (for FY2012) and for PT3. Given these uncertainties, we used as the initial forecast of changes in BCFS prices for PT3 (and last year of PT2), being the allowed increases in the price caps.

[40] Note that while BCFS decreased fares in the marketplace, the price caps did not decrease. The provisional PT3 price cap decision of 31 March 2011 took the effect of the duty remission into account.

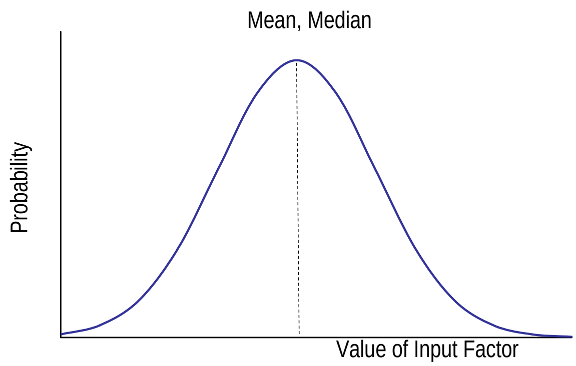
4.4 The risk factors used for the analysis

4.4.1 Probability Distributions

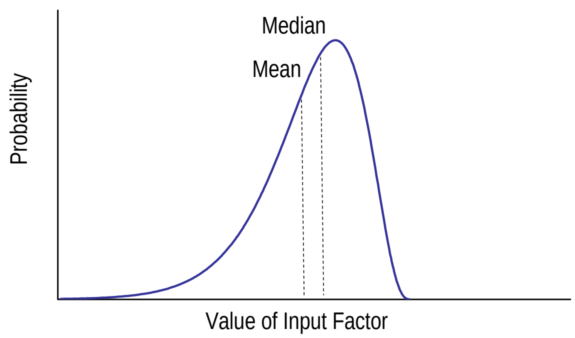
As indicated above, in quantitative risk analysis, values and probability distributions must be established for each forecast variable (economic growth, fuel prices, etc.). The probability distribution applied to each factor will affect the range of values generated and the probability of different values occurring. Commonly used distributions include:



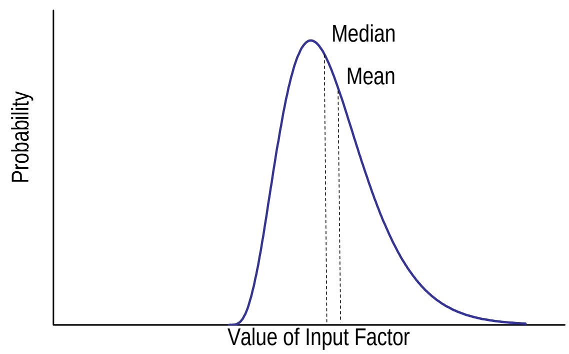
Uniform Distribution: A range of values between a specified maximum and minimum, all equally likely to occur.



Normal Distribution: A symmetrical distribution centered around the mean (expected) value. Values further away from the mean are less likely to occur than values near to the mean. Values below the mean are just as likely to occur as values above the mean.



Left-tailed (Gamma) Distribution: A non-symmetrical distribution skewed to the right with a long left-hand tail. Values below the median are just as likely to occur as values above the median. Smaller relative impacts (in absolute value terms) on the left side cause the median to be larger than the mean.



Right-tailed Distribution: A non-symmetrical distribution skewed to the left with a long right-hand tail. Values below the median are just as likely to occur as values above the median. Larger relative impacts (in absolute value terms) on the right side cause the median to be smaller than the mean.

4.4.2 Stochastic risk analysis of the BCFS traffic forecasts

Figure 4-1 outlines the factors selected affecting traffic development and the probability distributions applied. The identification of these factors was a result of the econometric analysis described above and the expert judgment of the study team.

Using these distributions, forecasts were generated for 10,000 iterations of the Monte Carlo simulation. The results of this analysis are provided in the following sections.

Figure 4-1: Forecast Risk Factors

Factor	Comments	Applied to the Following Routes	Distribution Details
British Columbia Economy	Forecast GDP growth up to 2016. • Based on average of five forecasts (4 banks plus BC MoFin). • Variance based on historical variance of BC GDP from past 10 years and expert judgement.	▪ Majors ▪ Route 3 ▪ North ▪ Minors	▪ Normally distributed ▪ Mean value of 2.8% per annum ▪ 5th percentile: -1.2% 95th percentile: 5.2%
Stagflation Factor	Switch variable reflecting a prolonged period of slow growth in the BC economy due to national, global and/or local factors [41] Variable is defined as a rate of growth below normal growth. • Factor is based on expert opinion	▪ Majors ▪ Route 3 ▪ North ▪ Minors	▪ Probability of occurrence: 2% (once every 50 years) ▪ Stagnation duration: 5 years [42] ▪ Impact (reduction below typical growth) is Normally distributed with a mean value of 1.0% below forecasted GDP growth,

[41] Examples of stagflation: Japan – 0.92% average annual growth in the period from 1991 to 2003; U.S. – 2.0% average annual growth in the period from 1973 to 1982 including four years of negative growth.

[42] Longer durations are possible, but irrelevant for a forecast that only goes to 2016.

Factor	Comments	Applied to the Following Routes	Distribution Details
	based on a Delphi session with economic experts		with and variance where: 5th percentile is 1.5% below, 95th percentile is 0.5% below.
Prices (1)	The ferry traffic demand model depends on the price which will be charged in the future for BCFS services. • The price forecasts are currently the preliminary price cap established by the Commission in its report of 31 Mar 2011. • The forecast model allows BCFS prices to randomly vary to reflect possible increases due to oil price increases. • The range is based on inspection of BCFS price index data for PT1 and PT2	▪ Majors ▪ Route 3	▪ Mean value of 4.15% growth per annum, per price cap draft of 31 Mar 2011 ▪ Right-tailed (gamma) distribution, to reflect the possibility that very high oil prices increases the mean price for BCFS services above the Commission's draft determination for PT3 ▪ Variance: 5th percentile is 1.5% price growth for BCFS service (2.65% below draft price cap) ▪ 95th percentile is 8.0%
Prices (2)	Same description as above, but for the case of Minor and North route groups as per the legislation introduced by the Province	▪ North ▪ Minors	▪ Mean value of 4.15% in year 1 of PT3 and 8.23% growth per annum thereafter ▪ Variance: 5th percentile is 2.0% 95th percentile is 13.0%
Terrorism (1)	Major terrorism event in North America, targeting transportation infrastructure but not BCFS specifically. • Based on InterVISTAS analysis of aviation and cruise ship events, with expert judgement.	▪ Majors ▪ Route 3 ▪ North ▪ Minors	▪ Probability of event: 5% (once every 20 years) ▪ Impact (percentage reduction in traffic) is Normally distributed with a mean value of 2% reduction in annual traffic ▪ and variance where: 5th percentile is 1% reduction ▪ 95th percentile is -5% ▪ Recovery time (time taken to recover all the traffic lost as a result of the terrorism event): 4 quarters.
Terrorism (2)	Terrorism event targeting a West Coast ferry operator • Based on judgement of InterVISTAS, which has researched incidence of terrorism	▪ Majors ▪ Route 3 ▪ North ▪ Minors	▪ Probability of event: 2% (once every 50 years) ▪ Impact (percentage reduction in traffic) is Normally distributed with a mean value of -20% and variance where: [43]

[43] We note that it is not expected that a terrorism event will result in the loss of all, or even most traffic. The impacts are annual impacts, and while there may be an immediate loss of all or most traffic, the lack of alternative affordable transportation options

Factor	Comments	Applied to the Following Routes	Distribution Details
	events.		▪ 5th percentile is -10% 95th percentile is -30% ▪ Recovery time (time taken to recover all the traffic lost as a result of the terrorism event): 8 quarters.
Accident	Operational incident on BCFS or another ferry operator leading to a loss of capacity or loss of confidence by travelling public • Based on historical record and judgement	▪ Majors ▪ Route 3 ▪ North ▪ Minors	▪ Probability of event: 2% (once every 50 years) ▪ Impact (percentage reduction in traffic) is Normally distributed with a mean value of -20% and variance where: 5th percentile is -10% 95th percentile is -30% ▪ Recovery time (time taken to recover all the traffic lost as a result of the incident event): 4 quarters.[44]
Air Mode Incident	An accident or operational issues on the seaplane or helicopter services leads to some traffic transferring to ferries. • Based on expectation that there could be a broad response affecting traffic of more than one air carrier for a transition period.	▪ Majors ▪ Route 3	▪ Probability of event: 2% (once every 50 years) ▪ Impact is Right-tailed (gamma) distributed with a mean value of 45,000 passengers per quarter ▪ and variance where: 5th percentile is 15,000 95th percentile is 100,000 ▪ Recovery time (time taken to for traffic to transfer back to air): 3 quarters.
High Tourism Growth	High growth in tourism	▪ Majors ▪ Route 3 ▪ North ▪ Minors	▪ Probability of occurring: 5% ▪ Tourism growth is Normally distributed with a mean value of +10% and variance where: 5th percentile is +5% 95th percentile is +15%

suggests that most traffic will return. Further, experience is that actual events are immediately followed by increased (although expensive and inconvenient) security measures.

[44] Recovery time depends on the nature of the incident. If it involves the loss of a vessel, redeployment of other vessels in the fleet may allow recovery of some capacity prior to vessel replacement, which typically is more than one year. If it involves only loss of confidence (e.g., if there is an incident on another ferry) recovery time may be quicker.

Using these distributions, forecasts were generated for 10,000 iterations of the Monte Carlo simulation. The results of this analysis are provided below.

4.5 Forecasting Results

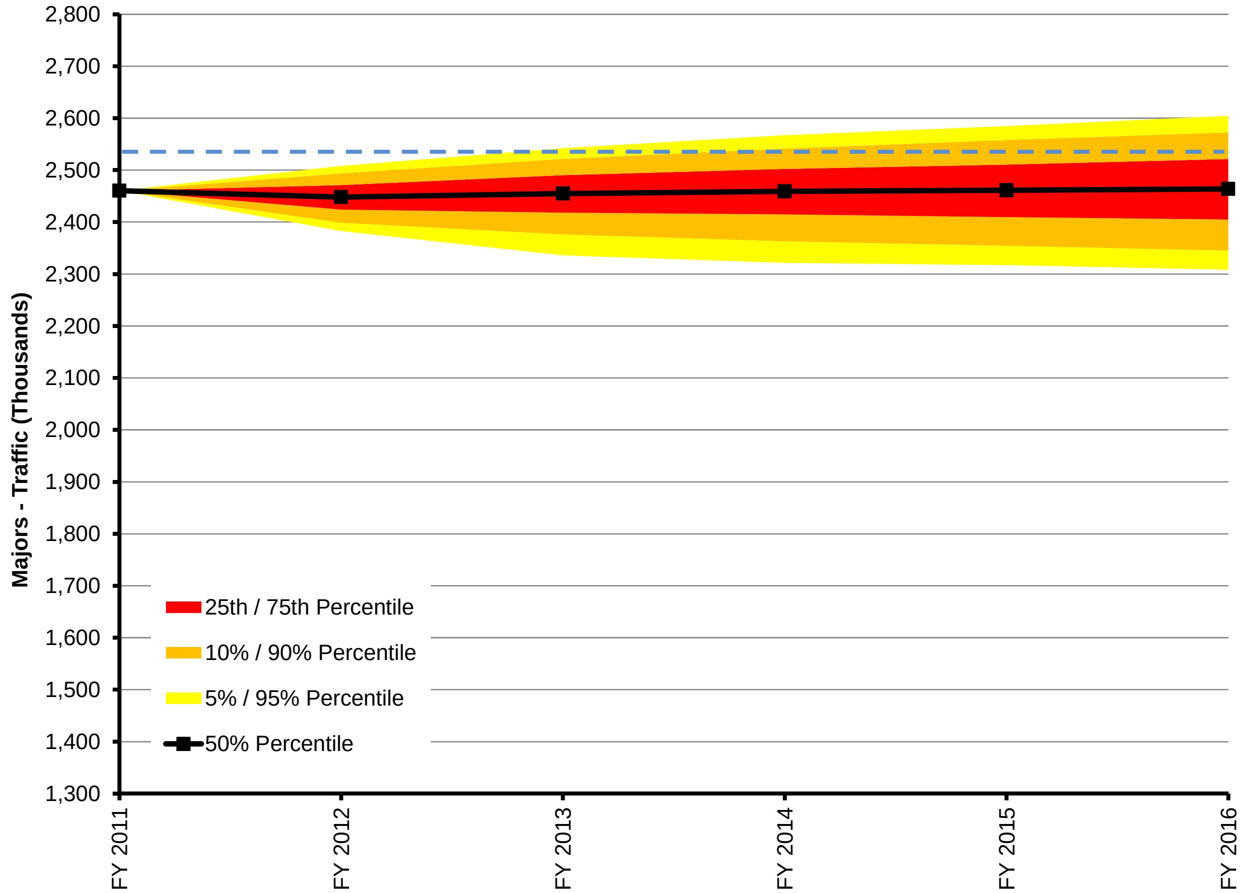
The forecasts are summarised in the following sections. Detailed tables of the forecasts are provided in Appendix F.

We note that in the charts showing the forecast results, the vertical scale differs across each of the route groups. When viewing these charts, the reader is cautioned to take into account the differences in the y-axis scaling when comparing forecast results between the route groups. What may appear as a large forecast range for one route group may be similar in percentage variation to other charts when considering the range of the vertical axes.

4.5.1 Majors

Using the distributions described in the previous section, forecasts were generated for 10,000 iterations of the Monte Carlo simulation. The 50th Percentile forecast (the median across the 10,000 iterations) produced is summarised in Figure 4-2, along with the percentile ranges. For example, in the annual data, the 50th Percentile forecast for the output traffic index for FY2016 is 2,463,600. The 5th percentile for FY2016 indicates that 5% of the forecast outcomes were less than 2,308,300 while the 95th percentile for FY2016 indicates that 95% of forecast outcomes were less than 2,604,400 (or 5% were greater than 2,604,400). The dashed blue line, superimposed on the forecast, represents the BCFS PT3 Forecast previously submitted to the Commission.

Figure 4-2: Forecast Results – Annual Traffic (Majors)



FY2011 = Year ending on 31st March, 2011.

Based on the risk analysis, the table below provides probabilities for different traffic outcomes in FY2016, e.g., the probability that, in FY2016, traffic will be less than or equal to current levels (49.2%). This is further illustrated in **Figure 4-3** which shows the distribution of forecast traffic volumes in FY2016 resulting from the 10,000 iterations of the Monte Carlo simulations. The blue line, superimposed on the forecast, represents the BCFS PT3 Forecast previously submitted to the Commission.

Figure 4-3: Probabilities of Various Traffic Outcomes – Majors

	Estimated Probability
Probability that FY2012 will be less than the PT3 Forecast (2,496,120)	88.9%
Probability that by FY2016…	
Traffic will be less than or equal to 2,300,000	5.4%
Traffic will be less than or equal to 2,400,000	23.3%
Traffic will be the same or less than FY2011 (2,460,387)	48.2%
Traffic will exceed 2,500,000	33.7%
Traffic will exceed 2,600,000	5.5%
Traffic will exceed 2,700,000	0.6%

Figure 4-4: Histogram of Forecast Traffic in FY2016 - Majors

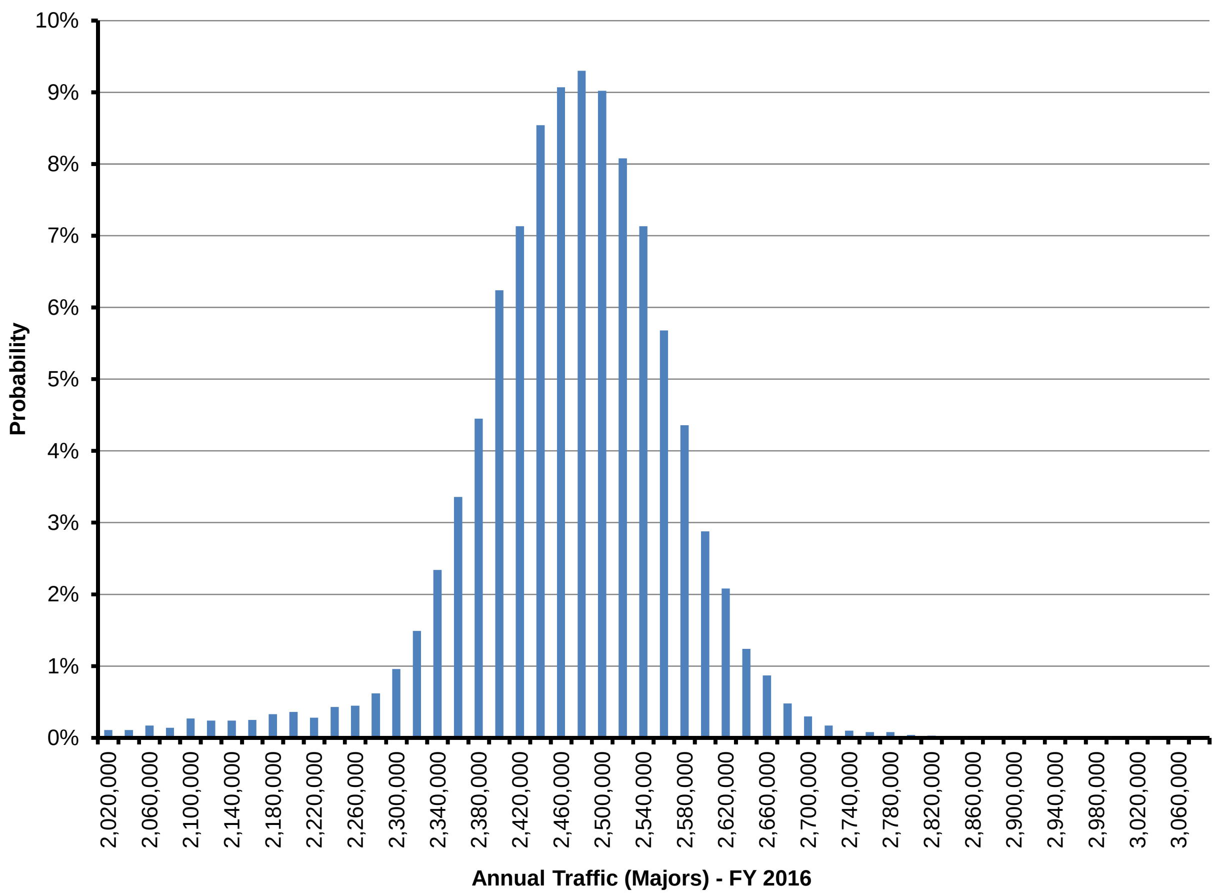
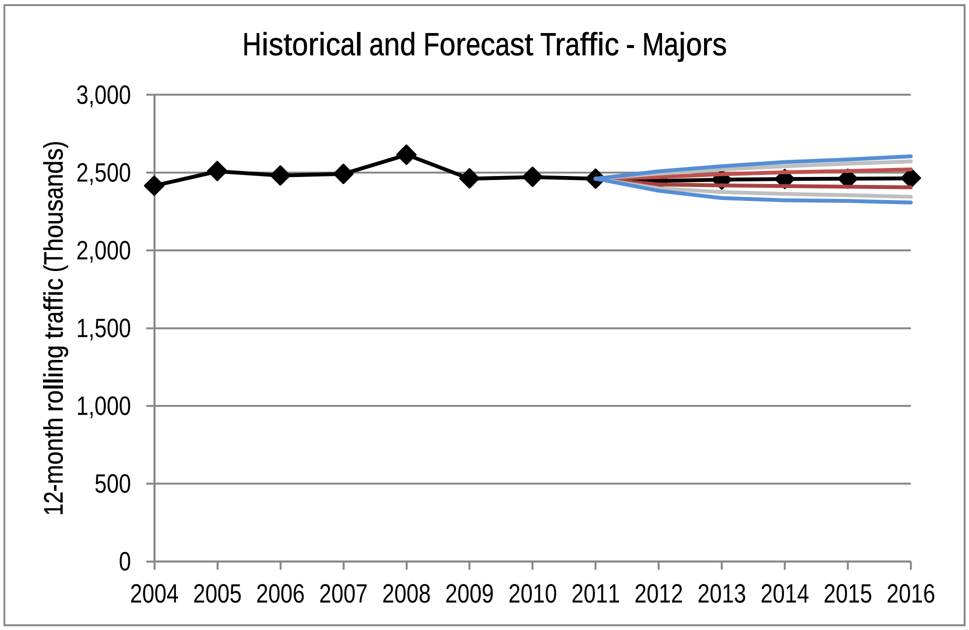


Figure 4-5a: Historical and Forecast Traffic - Majors

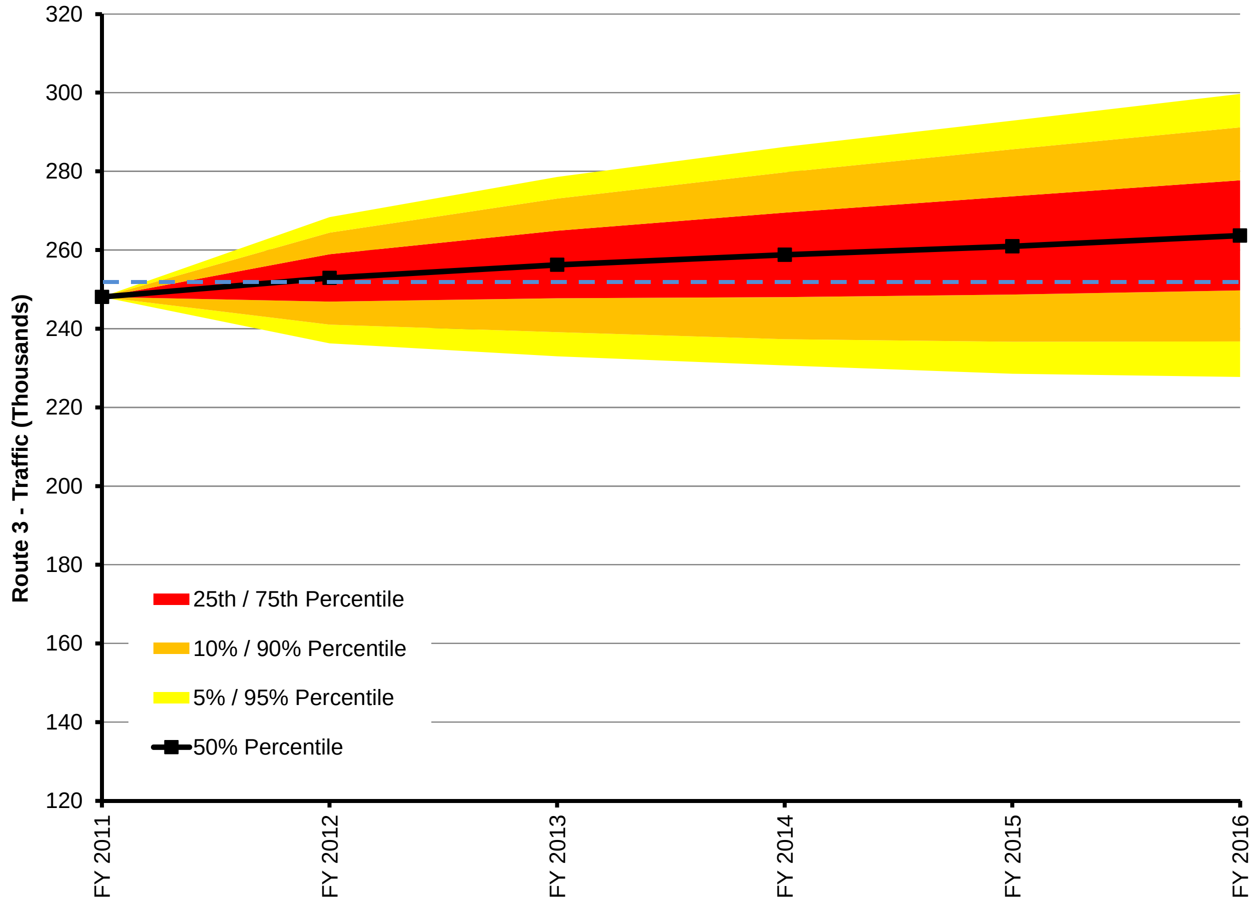


Fiscal_Year	Majors	Lower 5th Percentile	Lower 10th Percentile	Lower 25th Percentile	Upper 25th Percentile	Upper 10th Percentile	Upper 5th Percentile
2004	2,415,918						
2005	2,509,446						
2006	2,481,216						
2007	2,491,667						
2008	2,615,040						
2009	2,461,949						
2010	2,472,272						
2011	2,460,400	2,460,400	2,460,400	2,460,400	2,460,400	2,460,400	2,460,400
2012	2,448,000	2,382,900	2,398,900	2,423,900	2,471,000	2,493,500	2,508,100
2013	2,454,900	2,335,900	2,376,100	2,418,300	2,490,100	2,521,700	2,542,300
2014	2,458,900	2,321,500	2,363,100	2,414,900	2,502,200	2,541,200	2,567,200
2015	2,461,300	2,317,200	2,354,500	2,409,400	2,510,600	2,558,000	2,584,800
2016	2,463,600	2,308,300	2,345,000	2,405,000	2,521,300	2,572,400	2,604,400
	0.0%	-1.3%	-1.0%	-0.5%	0.5%	0.9%	1.1%

4.5.2 Route 3

The forecast results for Route 3 are provided in **Figures 4-6 to 4-9**.

Figure 4-6: Forecast Results – Annual Traffic (Route 3)



FY2011 = Rolling 12-Month Summation at the end of the Year ending on 31st March, 2011.

The dashed blue line, superimposed on the forecast, represents the BCFS PT3 Forecast previously submitted to the Commission.

Figure 4-7: Probabilities of Various Traffic Outcomes – Route 3

	Estimated Probability
Probability that FY2012 will be less than the PT3 Forecast (250,886)	41.0%
Probability that by FY2016…	
Traffic will be less than or equal to 230,000	5.8%
Traffic will be less than or equal to 240,000	12.9%
Traffic will be the same or less than FY2011 (248,100)	22.6%
Traffic will exceed 270,000	38.3%
Traffic will exceed 280,000	22.0%
Traffic will exceed 290,000	10.9%
Traffic will exceed 300,000	4.9%

Figure 4-8: Histogram of Forecast Traffic in FY2016 (Route 3)

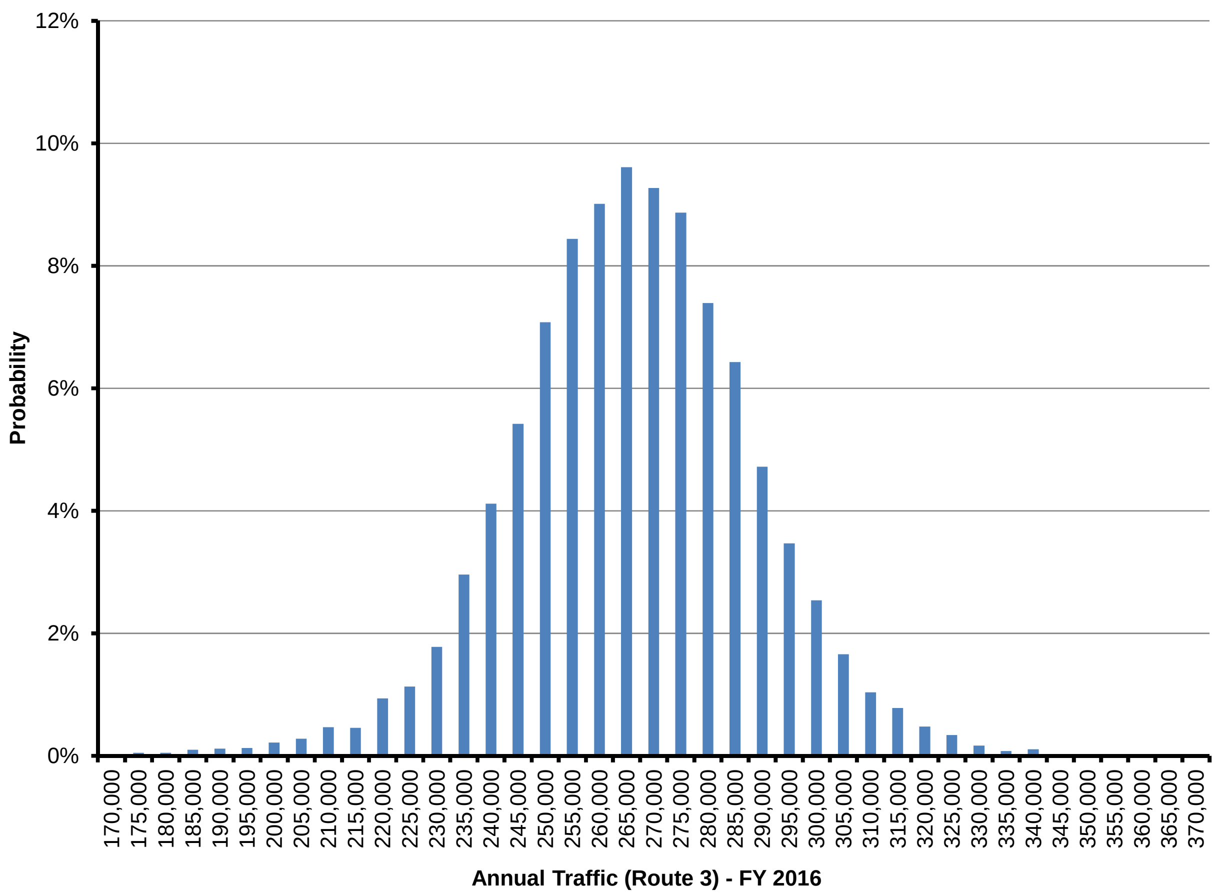
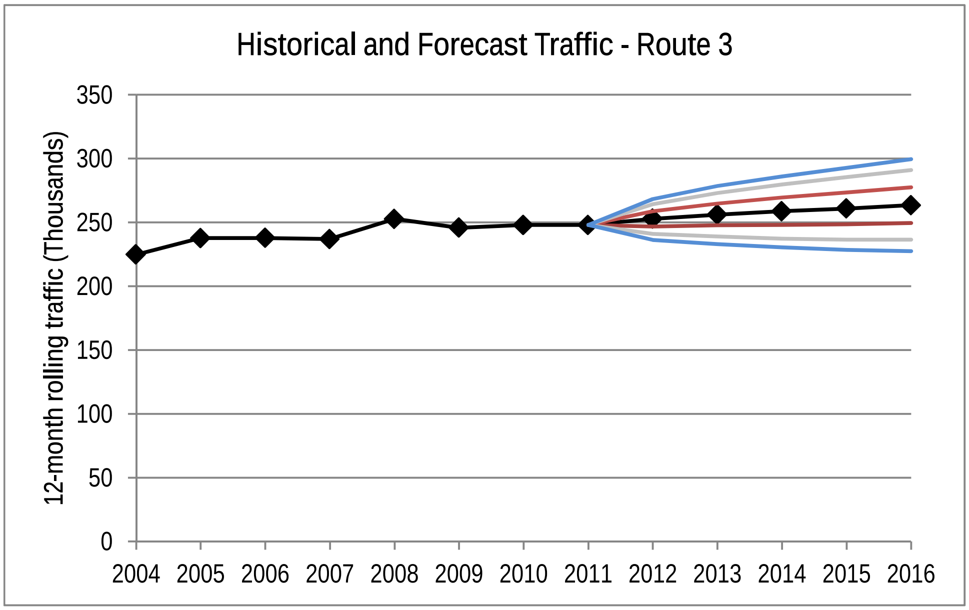


Figure 4-9a: Historical and Forecast Traffic in FY2016 (Route 3)

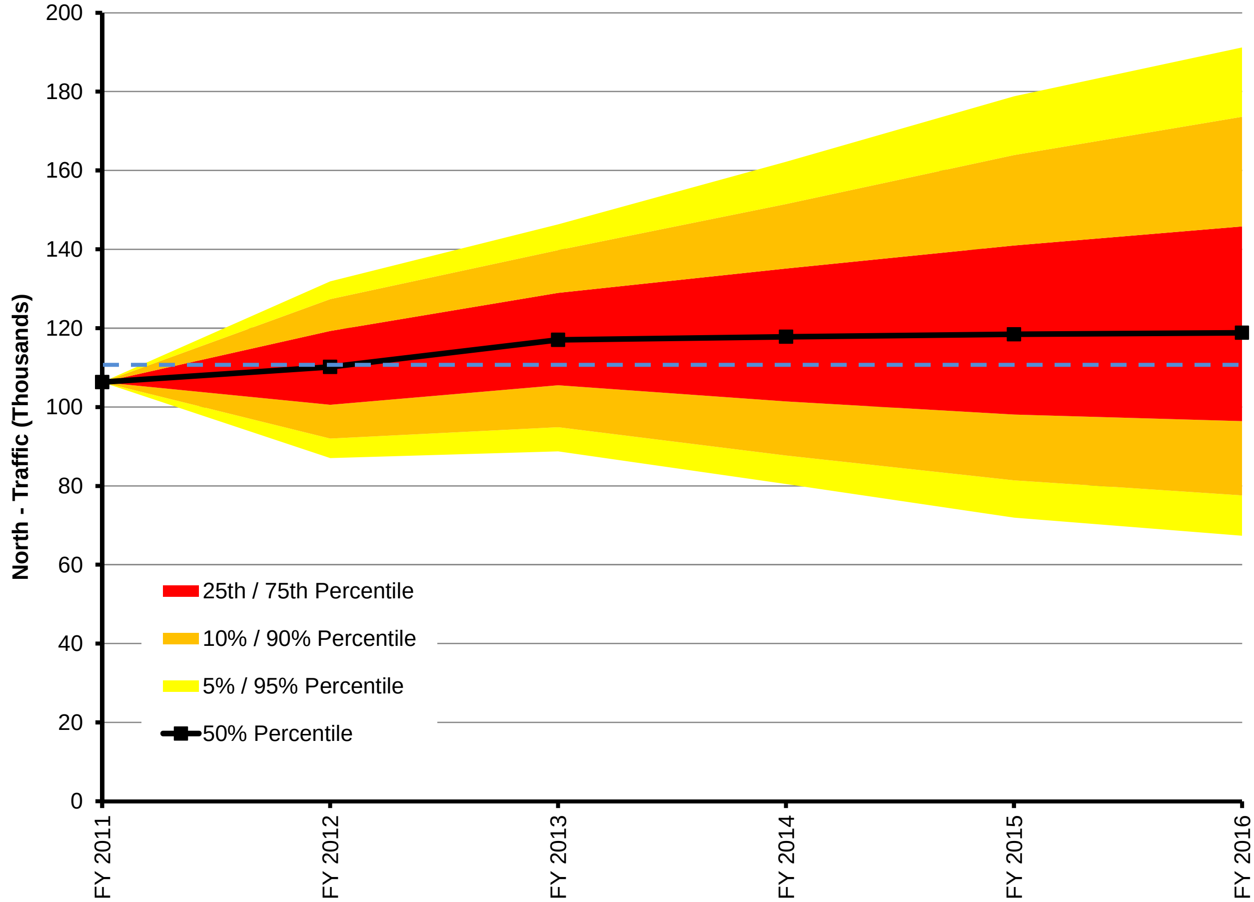


Fiscal_Year	Route 3	Lower 5th Percentile	Lower 10th Percentile	Lower 25th Percentile	Upper 25th Percentile	Upper 10th Percentile	Upper 5th Percentile
2004	224,866						
2005	237,817						
2006	237,913						
2007	237,088						
2008	252,824						
2009	245,897						
2010	248,103						
2011	248,100	248,100	248,100	248,100	248,100	248,100	248,100
2012	252,900	236,300	241,000	246,900	258,900	264,400	268,300
2013	256,200	233,000	239,100	247,800	264,900	273,100	278,600
2014	258,800	230,700	237,300	248,000	269,500	279,800	286,200
2015	260,900	228,600	236,700	248,700	273,600	285,600	292,900
2016	263,600	227,700	236,700	249,700	277,700	291,200	299,700
	1.2%	-1.7%	-0.9%	0.1%	2.3%	3.3%	3.9%

4.5.4 North

The forecast results for the North are provided in **Figures 4-10 to 4-13**.

Figure 4-10: Stochastic Forecast Results – Annual Traffic (North)



FY2011 = Year ending on 31st March, 2011.

The dashed blue line, superimposed on the forecast, represents the BCFS PT3 Forecast previously submitted to the Commission.

Figure 4-11: Probabilities of Various Traffic Outcomes – North

	Estimated Probability
Probability that FY2012 will be less than the PT3 Forecast (106,845)	41.1%
Probability that by FY2016…	
Traffic will be the same or less than 75,000	8.4%
Traffic will be the same or less than 100,000	28.8%
Traffic will be the same or less than FY2011 (106,277)	35.6%
Traffic will be the same or more than 125,000	43.6%
Traffic will be the same or more than 140,000	22.0%
Traffic will be the same or more than 130,000	9.4%

Figure 4-12: Histogram of Forecast Traffic in FY2016: North

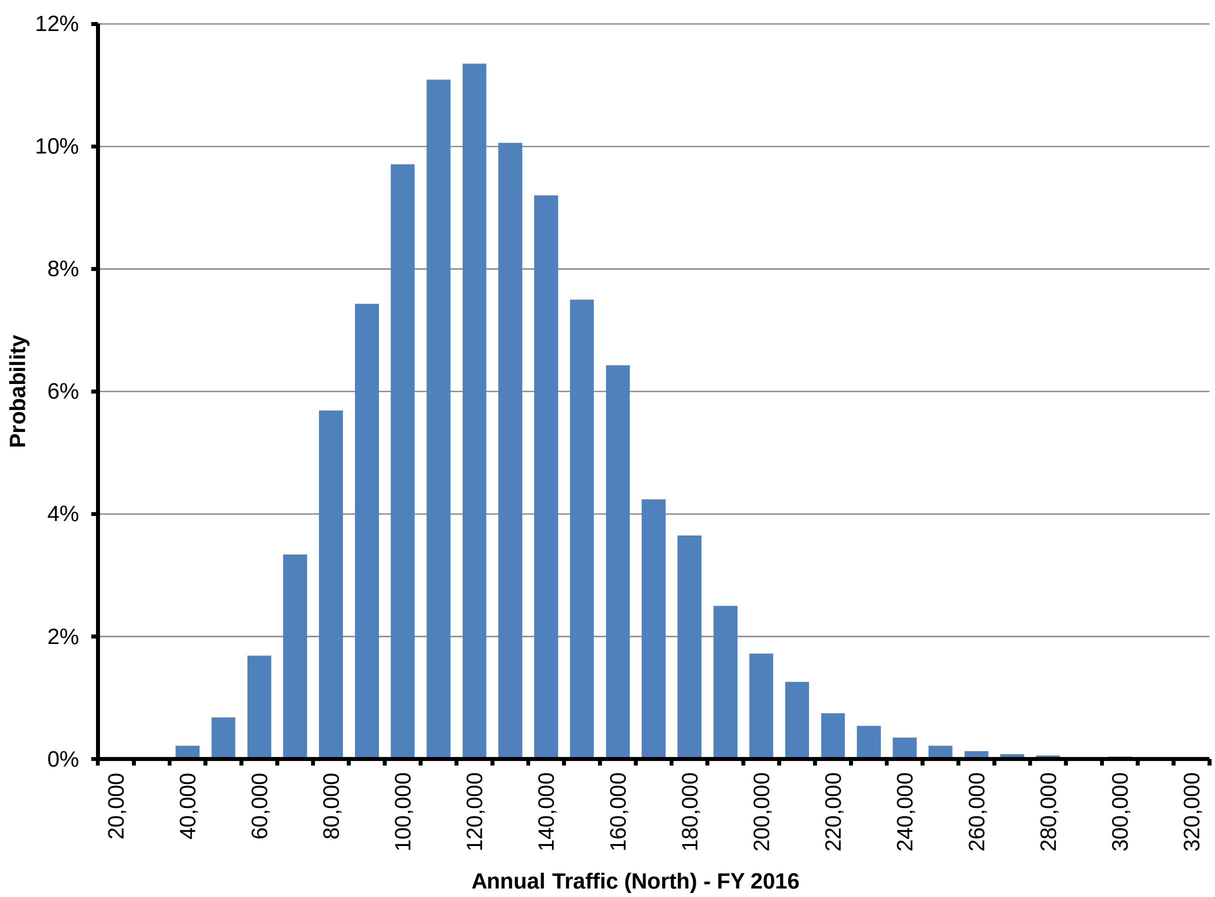
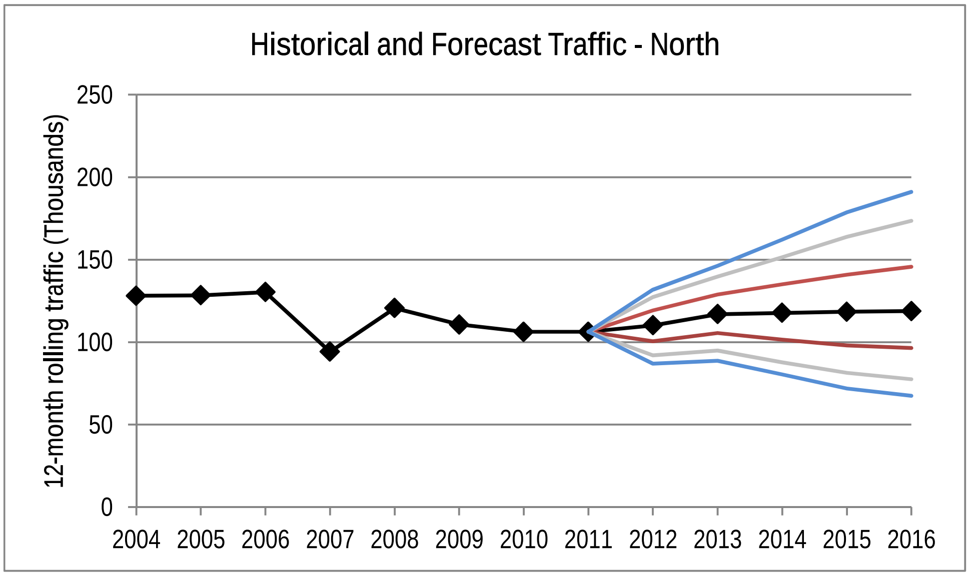


Figure 4-13a: Historic and Forecast Traffic in FY2016: North

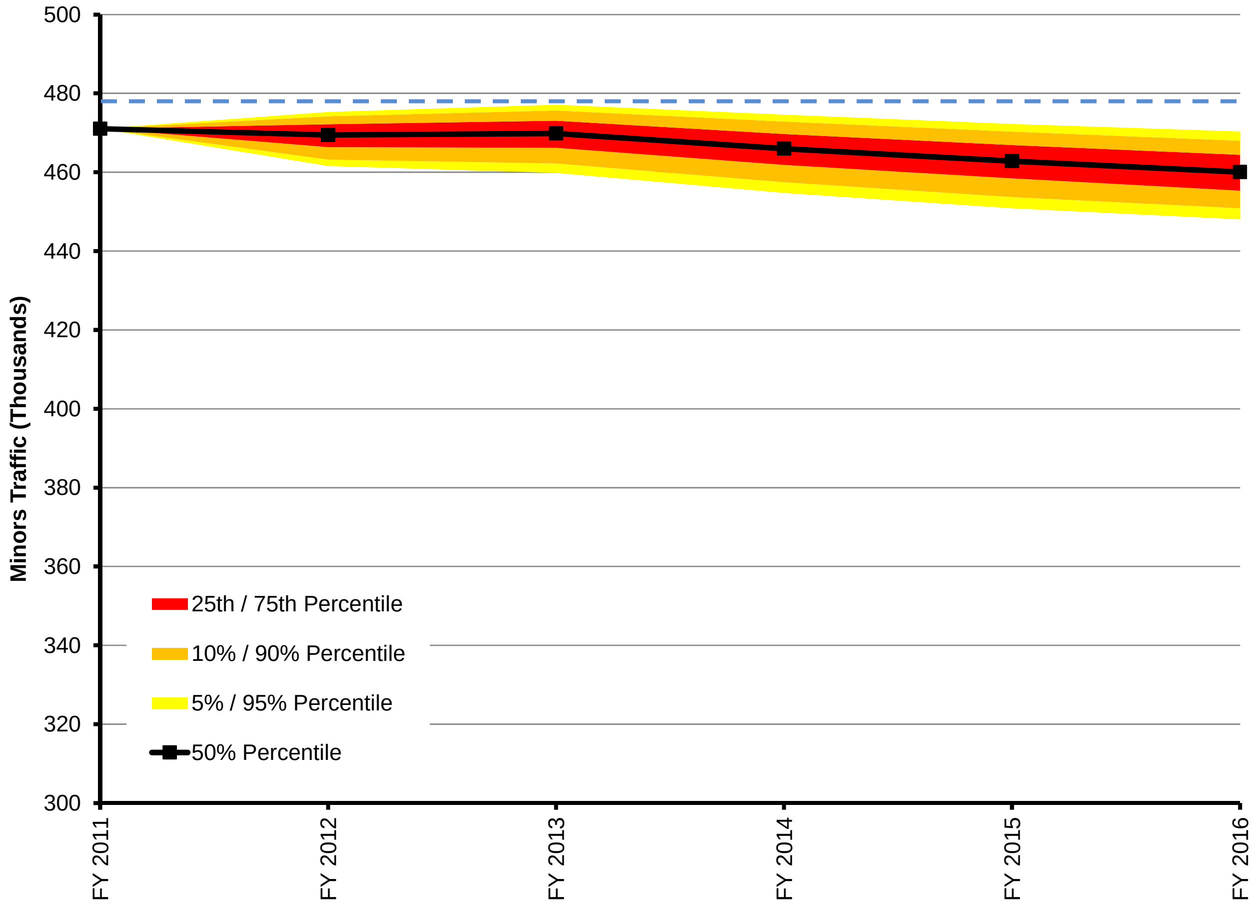


Fiscal_Year	North	Lower 5th Percentile	Lower 10th Percentile	Lower 25th Percentile	Upper 25th Percentile	Upper 10th Percentile	Upper 5th Percentile
2004	128,085						
2005	128,391						
2006	130,357						
2007	94,230						
2008	120,634						
2009	110,694						
2010	106,277						
2011	106,300	106,300	106,300	106,300	106,300	106,300	106,300
2012	110,200	87,000	92,000	100,600	119,300	127,400	131,900
2013	117,000	88,800	94,900	105,500	129,000	139,800	146,300
2014	117,800	80,500	87,700	101,400	135,100	151,500	162,200
2015	118,400	71,900	81,400	98,100	141,000	163,900	178,800
2016	118,800	67,400	77,600	96,400	145,800	173,600	191,200
	2.2%	-8.7%	-6.1%	-1.9%	6.5%	10.3%	12.5%

4.5.5 Minors

The forecast results for the Minors are provided in **Figures 4-14 to 4-17**.

Figure 4-14: Stochastic Forecast Results – Annual Traffic (Minors)



FY2011 = Year ending on 31st March, 2011.

The dashed blue line, superimposed on the forecast, represents the BCFS PT3 Forecast previously submitted to the Commission.

Figure 4-15: Probabilities of Various Traffic Outcomes – Minors

	Estimated Probability
Probability that FY2012 will be less than the PT3 Forecast (488,326)	98.9%
Probability that by FY2016…	
Traffic will be less than or equal to 400,000	1.0%
Traffic will be less than or equal to 425,000	2.0%
Traffic will be less than or equal to 450,000	8.6%
Traffic will be the same or less than FY2011 (471,055)	96.2%
Traffic will exceed 465,000	22.0%
Traffic will exceed 475,000	0.7%

Figure 4-16: Histogram of Forecast Traffic in FY2016: Minors

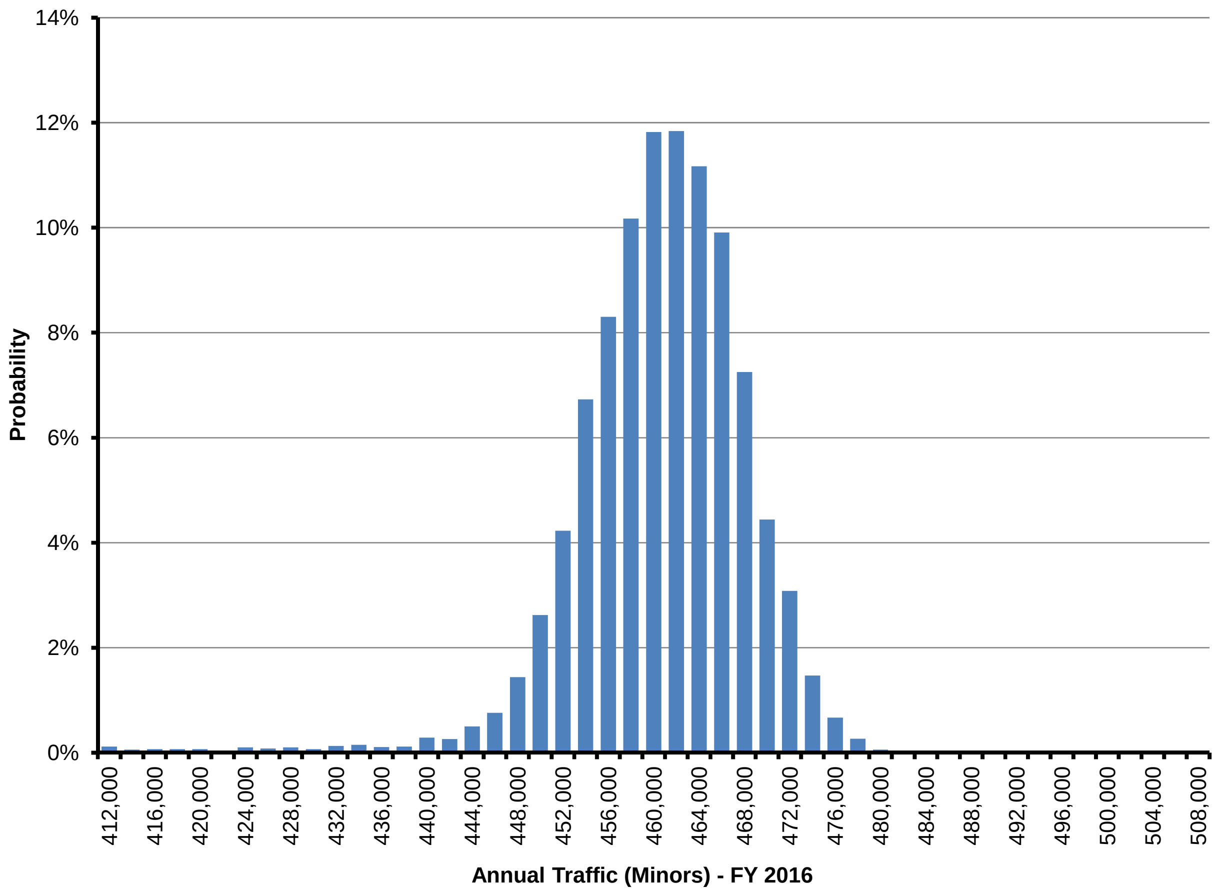
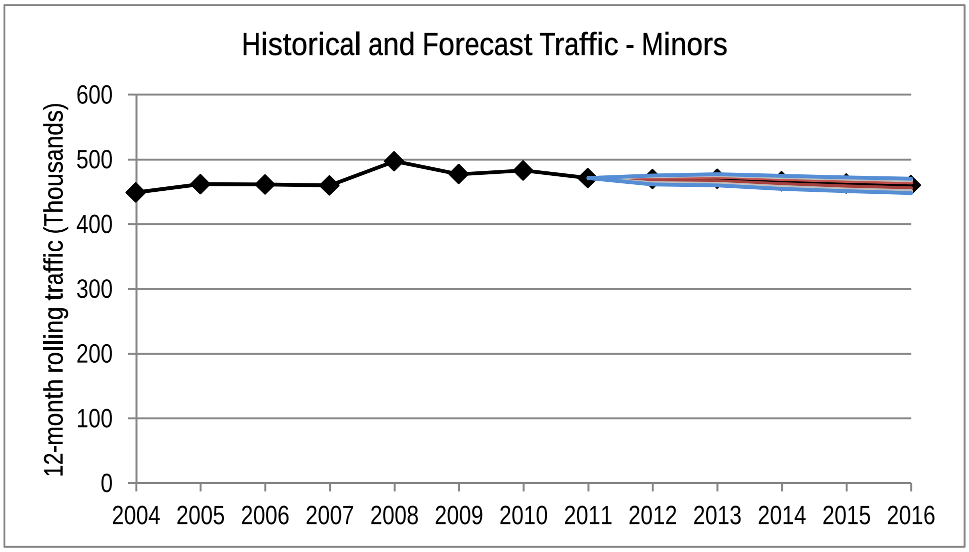


Figure 4-17a: Historic and Forecast Traffic in FY2016: Minors



Fiscal_Year	Minors	Lower 5th Percentile	Lower 10th Percentile	Lower 25th Percentile	Upper 25th Percentile	Upper 10th Percentile	Upper 5th Percentile
2004	448,992						
2005	461,739						
2006	461,246						
2007	459,856						
2008	497,282						
2009	477,318						
2010	482,822						
2011	471,100	471,100	471,100	471,100	471,100	471,100	471,100
2012	469,400	461,600	463,200	466,400	472,200	474,200	475,300
2013	469,800	459,800	462,200	466,200	473,100	475,700	477,100
2014	466,000	454,700	457,500	461,800	469,700	472,800	474,600
2015	462,800	450,800	453,700	458,400	466,900	470,300	472,300
2016	460,000	448,100	450,900	455,300	464,400	468,000	470,300
	-0.5%	-1.0%	-0.9%	-0.7%	-0.3%	-0.1%	0.0%

5.0 Cross Price Elasticity: Price Elasticity of Demand Estimation and Net Traffic Stimulus

5.1 Price elasticity

In economics, elasticity measures the response or sensitivity of one economic variable to the change in another economic variable. Elasticities are a useful concept as they allow decision makers insight into the impact of different economic actions. A common elasticity concept is the price elasticity of demand. This measures the percentage change in quantity demanded of a particular good or service as result of a percentage change in the price of the good or service.

The price elasticity is defined as:

$$\text{Price Elasticity} = \frac{\%\ \text{Change in Quantity Demanded}}{\%\ \text{Change in Price}}$$

For example, suppose a good has a price elasticity of -0.6; a 10% increase in the price will result in a 6% decline in the quantity demanded. For a good with a price elasticity of -1.2, a 10% increase in the price will result in a 12% decline in the quantity demanded.

Since the quantity demanded decreases when the price increases, the price elasticity is expected to be negative.

Goods or services with elasticities less than one in absolute value are commonly referred to as having inelastic demand – the proportional change in quantity demanded will be less than the proportional change in price. In this situation, increasing the price will increase the revenue of the producer of the good, since the revenue lost by the relatively small decrease in quantity is less than the revenue gained from the higher price.

5.2 Cross price elasticity

Economists also use a concept called the cross price elasticity. This measures how the quantity demanded of one good changes when the price of another good changes. Two cases are distinguished:

- Substitutes
  An example of substitutes might be hot dogs versus hamburger. When the price of hamburger rises, the demand for hot dogs increases, as some consumers are willing to substitute hot dogs for the now more expensive hamburgers. The cross price elasticity of substitutes is positive – an increase in the price of hamburger *increases* the demand for hot dogs.

- Complements
  An example of goods that are complements are hamburger and hamburger buns. When the price of hamburger increases, demand for hamburger buns decreases. The cross price elasticity of goods that are complements is negative.

The cross price elasticity is defined as:

- Price Elasticity = $\frac{\text{\% Change in Quantity Demanded of good B}}{\text{\% Change in Price of good A}}$

5.3 Cross price elasticity for BCFS services

Transportation services are generally viewed as being unique for different days and different sailings. A person who lives in Victoria and has a 10am meeting in Vancouver wishes to buy service on the BCFS 7am sailing. The 9am sailing would be viewed by this person as a different service, perhaps one he/she is unwilling to purchase. Some consumers may be willing to *substitute* the 9am sailing for their preferred 7am sailing. They might be induced to do so if the price of the 9am sailing is lower than the 7am sailing. Similarly, some consumers may be willing to substitute sailings on different days. Someone who planned on travelling on a Friday sailing at the beginning of a long weekend, might be induced to travel on the Thursday if sailings on that day have discounted prices.

When considering the issue of the price elasticity for BCFS services, we can distinguish between two cases:

- A decrease in price for a specific sailing on a specific day increases traffic on that sailing, with the incremental traffic constituting an increase in the total demand for ferry services.

- A decrease in price for a specific sailing on a specific day increases traffic on that sailing, but does so by diverting passengers from other sailings with no increase in overall demand for ferry services.

The use of quarterly data on traffic and price for BCFS route groups will not distinguish between these two types of price impacts. This is because the data aggregates (or sums up) all the traffic on all sailings in the route group, and does not distinguish between days or sailings within a given day.

We can nevertheless investigate these phenomena by utilising data on daily traffic for a route group. This will not give us information on consumer substitution between sailings on a given day when some sailing are price discounted and other are not. It will allow us to observe whether some consumers will substitute sailings on different days.

Our approach is to estimate a demand equation for daily traffic using 2SLS. BCFS was able to provide us with daily traffic on the route group,[45] and daily revenues. By dividing the latter by the former, we can construct yield, or the average price paid. We were also provided data on days when discounts (in the form of CoastSaver fares) were available.

Merely including price in the demand equation would not distinguish between these two types of price impacts. To capture the impact, we introduced indicator variables for days immediately before and after the discounts.[46] If the price discounts only stimulate traffic, we would expect that traffic immediately before/after a discount episode would be as usual. However, if the discounts are causing some travellers to substitute

[45] We confined our analysis to passenger traffic on the Majors route group.

[46] We used two indicators: one to indicate the day immediately preceding and immediately following an episode of price discount; and one to indicate the day two days prior (and two days after) an episode of discount.

travel on a day with lower price for travel on a more expensive day, then the indicator variables should be negative, as higher travel on the discount days would result in lower travel on the immediately preceding/following days.

5.4 Regression results

The demand model for use with daily data needs to control for seasonality (which we did by indicator variables for months) and day of week effects. As well, we include variables to indicate the shift to higher demand on days that are holidays (or weekend days associated with a holiday), and the days immediately preceding or following a holiday weekend, when demand also increases. We included the all-in price for service on each day. We did not include GDP, as the data set we used only covered two years and data on BC GDP is only available annually.

Figure 5-1 provides the regression coefficients for our model using daily data.

Figure 5-1: Regression Coefficients Using Daily Data

Variable	Coefficient	Standard Error	T-statistic
Constant	9.804	0.237	41.4
Price [47]	-0.146	0.097	-1.5
CoastSaver effect			
Dummy – 1 day pre/post CoastSaver discount	-0.026	0.022	-1.2
Dummy – 2 days pre/post CoastSaver discount	-0.015	0.021	-0.7
Indicators for holidays			
Dummy – holiday	0.317	0.020	15.7
Dummy – 1 day pre/post holiday	0.338	0.024	14.0
Dummy – 2 days pre/post holiday	0.218	0.025	8.9
Dummy – 3 days pre/post holiday	0.153	0.024	6.3
Indicators for day of week			
Sun	0.150	0.018	8.1
Mon	-0.399	0.019	-20.7
Tue	-0.593	0.019	-31.5

[47] This is the all-in price for adults. Investigation indicated that child and senior fares are generally proportional to the adult fare.

Variable	Coefficient	Standard Error	T-statistic
Wed	-0.563	0.019	-29.2
Thu	-0.409	0.019	-21.8
Fri	0.015	0.019	0.8
Sat[48]	-	-	-
Indicators for months			
Jan	-0.194	0.025	-7.7
Feb	-0.019	0.025	-.07
Mar	0.100	0.025	4.1
Apl	0.193	0.027	7.1
May	0.300	0.024	12.3
Jun	0.455	0.026	17.4
Jul	0.666	0.024	27.3
Aug	0.733	0.026	28.5
Sep	0.385	0.027	14.1
Oct	0.143	0.029	5.0
Nov	-0.057	0.028	-2.0
Dec[49]	-	-	-
R-square: 0.86 *1096 observations*			

Some observations can be made from the above:

- The price elasticity is of correct sign (negative) and is relatively inelastic (elasticity = -0.15).

- The price elasticity estimate is borderline significant. With the daily data, there are over 1000 data points and there is significant price variation in the data. The finding of a border line significance of

[48] Saturday is the reference category for the days of the week variables and is omitted from regressions. The omitted category becomes the reference category against which the effects of other days of the week are interpreted.

[49] December is the reference category for the month variable and is omitted from regressions. The omitted category becomes the reference category against which the effects of other months are interpreted

price elasticity is consistent with price not being a strong determinant of ferry demand.

- The month and day of week indicators are highly significant. The month indicators can be interpreted as percentage changes relative to demand in December, and the day of week indicators are relative to Saturday. Sunday demand, for example, is generally 15% higher than on a Saturday.

- The holiday indictors are highly significant. In general:
    - Holiday traffic demand on any given day or month is roughly 32% higher than demand on a similar day/month without a holiday.
    - The increase in traffic demand on the day immediately before/after a holiday is roughly the same as an increase in traffic demand for the holiday, 34% higher than regular days. While slightly higher than demand on a holiday, the confidence interval around the two indicators overlap and the effect could be the same.
    - Demand 2 days before/after is also higher than regular days, but not as strong at the holiday traffic increase, 22% higher than regular days.
    - Demand 3 days before/after further attenuates, 15% higher than regular days.

The indicators for the days immediately before/after a CoastSaver discount episode are very interesting:

- One day before/after has 2.6% lower demand than usual.
- Two days before/after has 1.5% lower demand than usual.
- These results have only weak statistical significance, and must be viewed with some caution. Nevertheless they are revealing and might suggest further analysis.

These results are consistent with the concept that fare discounts shift some demand from one sailing to another. That is, not all of the effect of a discount is to stimulate new demand. A large portion is merely demand shifting, from peak (non-discounted) periods to off peak periods.[50]

We can make further use of the information in the regression to assess whether fare discounting only shifts traffic or whether it also stimulates some new travel. To do this, we use the fare elasticity to compute the change in traffic on days with a price discount. We then use the CoastSaver before/after indicator variables to measure the offset in terms of reduced traffic on other days. Our computations are shown in Figure 1. In doing our computations we recognized that the effect of a given dollar amount of discount on the BCFS passenger charge has different percentage impacts for walk on travellers versus those who drive on with a vehicle.[51]

Figure 5-2 below calculates the net traffic stimulus of 3.10% due to the presence of a CoastSaver discount within a given period.[52] The results indicate that traffic roughly increases 3.5% per day that the CoastSaver

[50] We note that CoastSavers are used for two purposes. The first is to shift traffic demand from busy to off peak days. The second is to allow BCFS to reduce its total revenue in a given quarter if revenues in a previous quarter exceeded the allowance of its price cap.

[51] Further refinement of this computation could be made to adjust for passengers travelling on buses.

[52] The calculations in Figure 5-2 assume that there are on average of 1.5 passengers traveling in drive on vehicles and the split between walk on and drive on passengers 55/45 which has been calculated using data supplied by BCFS.

in effect. If the discount is offered for 3 consecutive days, which is common, then we might think of traffic being increased during that period by 10.5% equivalents of daily demand.[53] The CoastSaver pre/post indicators reduce demand on those days by roughly 7.5% equivalents of daily demand.[54] Thus, of the 10.5% traffic stimulation on discount days, roughly three-quarters of this (7.5%) appears to be shifting traffic from immediately adjacent days.

Figure 5-2: Net Traffic Stimulation from CoastSaver Discounts

Price Elasticity of Demand Calculation: Daily Data for adults on the major route

Daily Data: based on regression LN-DDMajor-111

27-Apr-2011

Data	**Base Fare**	**Traffic Split**
Avg. Walk on all in price	$ 12.78	0.55
Avg. Vehicle all in price	$ 42.60	0.45
Avg. passenger CoastSaver	$ 4.82	
Price Elasticity	**-0.146**	

	Price	**% Change Price**	**Elasticity**	**% Change Quantity**	**Share Weight**	**Per Day extension**
Walk On	$ 12.78	(37.72)	-0.146	5.51	0.55	3.03
Vehicle*	$ 61.77	(7.80)	-0.146	1.14	0.45	0.51
**Assuming 1.5 passengers*				**Weighted % Quantity Change**		3.54

Illustrative example		**%**	
	increased pax for 3 Days with CoastSaver	10.62	%
	shfit from 1 Day Before and After CoastSaver	(4.52)	%
	shift from 2 Days Before and After CoastSaver	(3.00)	%
	Net Traffic Stimulation	3.10	%

[53] 3 days times 3.5% per day.

[54] Two days with 2.6% reduction and two days with 1.5% reductions.

6.0 Are the Price Elasticity Estimates Sensible?

6.1 Introduction

Before concluding this report, we wish to return to the issue of price elasticity, as it is of critical importance in setting the price cap. Key observations are summarized, including findings from previous studies of elasticities. We then apply a common sense test on our elasticities.

6.2 Key observations on price elasticities for BCFS services

We begin with some key observations:

- This study has found that there is some price elasticity for the demand for BCFS services. Higher prices for BCFS services reduce demand for services from what it would have otherwise been, all things being constant. This is true whether the price increase is due to fuel surcharges, or due to higher fares resulting from the higher price caps put in place in PT1 and PT2 due to increases in BCFS costs (e.g., due to deployment of new ships, increased staffing requirements and other measures due to new safety and security measures, etc.).

- The analysis of daily data for the Majors indicates that when price discounts are put in place on selected sailings, traffic increases modestly on those sailings. Roughly two-thirds of this is due to shifting demand from other sailings (those without discounts) and one-third due to increased demand.

- The price elasticities found in this study, are modest in magnitude. All of our results are that the demand for ferry services is price inelastic in that a given percent increase in price results in a less than proportional drop in traffic. They estimated price elasticities range from -0.12 to -0.56. The highest elasticity (-0.56) is for the North. It is perhaps not surprising that this route group is found to have the most price elastic response, given that many of these routes are long with corresponding high costs and price. The Majors and Route 3 have similar price elasticities at -0.28. The Minors were found to have a price elasticity of -0.12.

- A recent study for the Commission suggested price elasticities of that range from -0.3 to -0.5 (specify for the route groups), depending on the route group (higher for major routes than for minor routes). That study also reported elasticity estimates from a series of other studies that range from -0.3 to -0.7.

- This (InterVISTAS) study and previous studies find the demand for BCFS services to be price inelastic, meaning the elasticities are in a range that are between 0 and -1.0. Price inelastic demands mean that while traffic will fall when price is increased, it will fall less than proportionally.

- While all studies find inelastic demand, this study is finding somewhat lower elasticities than previous studies.

6.3 A common sense test

We conduct a simple, but common sense test on our elasticity findings. (Some describe this type of test as a smell test of the results.) Price elasticity is the percentage change in traffic divided by the percentage change in price. There are many subtleties to computing elasticities, including the need to control for other factors (e.g., the onset of an economic recession) that may also have contributed to an observed change in traffic. Nevertheless, a crude computation of the ratio of the actual percentage change in BCFS traffic since 2003 to the percentage change in BCFS prices was undertaken. While we do not represent this to be a correct elasticity measure, it can be used as a rough order of magnitude check against the elasticity estimates we obtained in Section 3.3. If, for example, the rough order of magnitude check is a ratio of say -1.00, while our elasticity estimate in Section 3.3 is only -0.23, then it would cause us some concern unless we can explain the larger drop in traffic used in the order of magnitude test as being due to other (non-price) factors.[55]

Figure 6-1 performs this order of magnitude check for each of the route groups.

Figure 6-1: Simple Elasticity Calculations from FY2004Q4 to FY2011Q4[56]

Route Group	FY2004Q4 to FY2011Q4 % Price Change	FY2004Q4 to FY2011Q4 % Traffic Change	Ratio *(order of magnitude check)*	Elasticity *as estimated in Section 3.3*
Major	42%	-5%	-0.13	-0.28
Route 3	57%	-3%	-0.05	-0.28
North	61%	-16%	-0.26	-0.55
Minor	65%	-6%	-0.09	-0.12

We observe that while the rate of percentage changes in traffic to percentage changes in price are not the same as the elasticities we estimated, they are roughly in the same order of magnitude.

There is another way we could look at this issue. Some may claim that the demand for ferry traffic is much more price elastic than our findings in Section 3.3. We can use the claimed elasticities along with the actual changes in BCFS prices to compute what the implied change in traffic should be. Consider the Major route group:

- From FY2004Q4 to FY2011Q4, BCFS average price grew 42%.[57]

[55] There are many factors affecting demand for BCFS services, and the simple order of magnitude test could overstate or understate the true elasticity. Perhaps the main factors that also affected BCFS traffic since 2003 was the major decline in traffic from the 2007-2008 recession, and any potential impacts of higher fuel prices. Because both of these factor are demand reducing, our rough and ready test of price elasticity will overestimate the actual price elasticity, because it will try to attribute all the decline in BCFS traffic demand to higher prices, even the declines due to recession and higher fuel prices.

[56] To avoid seasonal differences in traffic from distorting our ratio computation, we computed the percentage changes in traffic (and corresponding percentage changes in price) for the same quarter. Here, we took the most recent data (March 2011, which was FY2011Q4) and compared it to the earliest data for the same quarter (FY2004Q4).

- If one postulates a higher price elasticity,[58] perhaps -0.7,
- Then this would suggest that traffic would have declined by 29.4%.[59]
- If there were other reasons that caused traffic to decline, e.g., economic recession and higher gasoline prices, then we would have expected the decline in traffic to be even higher than 29.4%.
- The actual decline in traffic on the Majors was only 5%. This is much less than the decline in traffic which an elasticity of -0.7 would imply. Thus, the evidence is not consistent with an elasticity of -0.7.
- On the other hand, an elasticity of -0.28 would imply a drop in traffic in the range of 12%, which is much closer to actual 5% drop in traffic than the 29% drop indicated by a -0.7 elasticity.

Thus, we conclude that these types of common sense checks on our elasticity estimates in Section 3.3 support our estimates. The common sense checks do not support price elasticity estimates in the range of -0.7.

6.4 PT2 forecast and expected traffic impact

To further investigate the effects of changes in prices on traffic forecasts, we look backward at the traffic forecasts developed in 2007 by a consultant to BCFS for PT2. We compare these forecasts to actual PT2 traffic and then examine the role of price.

Figure 6-2 uses our elasticity estimates to compute the implied change in traffic from high prices for BCFS services. This is then subtracted from the 2007 traffic forecast as a rough indication of how the 2007 traffic forecast might be adjusted for the elasticity impact of higher prices. This then is compared to the actual traffic growth.

57 There are many reasons prices grew faster than inflation, including the large run up in fuel costs, costs of new safety and security measures and the costs of investing in and deploying several new, replacement vessels as well as undertaking deferred maintenance and overhauls of other vessels.

58 Technical point. Economists generally would say that an elasticity of -0.7 is a 'higher' elasticity than -0.28. A mathematician, however, would observe that -0.7 is less than -0.28. In this report we conform to conventional economics use of the adjective 'higher'.

59 -0.7 times 42% is -29.4%.

Figure 6-2: The Impact of Price Effects on 2007 PT2 Traffic Forecasts using Estimated Elasticities

Route Group	Actual % Price Change	Price Elasticity	PT2 Traffic Impact due to Price Change	2007 Forecast of Growth for PT 2	2007 Traffic Forecast less Price Impact on Traffic	Actual Traffic Change	Traffic Change Not Explained by Price Effect
Majors	15.3%	-0.28	-4.3%	2.0%	-2.3%	-2.8%	-0.5%
R3	17.9%	-0.28	-5.1%	2.6%	-2.5%	-0.2%	2.7%
North	19.0%	-0.56	-10.7%	1.0%	-9.7%	-5.8%	3.9%
Minors	18.9%	-0.12	-2.3%	1.9%	-0.4%	-2.6%	-2.2%

For the Majors:

- BCFS average fares rose from FY2009Q1 (April 1 2008) to FY2011Q4 (March 31 2011) by 15.3%.
- Using our price elasticity estimate of -0.28, this implies traffic could be expected to have fallen by 4.3% due to the price elasticity.
- The 2007 forecast for this period of time was for traffic growth of 2.0%.
- Removing the impact of higher prices (-4.3%), then the net traffic change would have declined by 2.3%.
- The actual change in traffic was -2.8%.

As can be seen for all four route groups, the 2007 forecast called for traffic growth of between 1.0% and 2.6%. The price elasticity impact was traffic reducing for all four route groups, ranging from traffic declines of 2.3% to 10.7%. Netting the price effect from the 2007 traffic forecast results in a value that differs from the actual traffic change ranging from 0.5% (Majors)[60] to 3.9% (North).

We do not want to place too much weight on this computation, as there are many other factors affecting traffic. It is merely intended as a rough check on our price elasticities.

We can repeat the computation using an alternative elasticity, to check its reasonableness. Figure 6-3 shows the computation using an elasticity of -0.7.

Figure 6-3: The Impact of Price Effects on 2007 PT2 Traffic Forecasts using Estimated Elasticities

Route Group	Actual % Price Change	Price Elasticity	PT2 Traffic Impact due to Price Change	2007 Forecast of Growth for PT 2	2007 Traffic Forecast less Price Impact on Traffic	Actual Traffic Change	Traffic Change Not Explained by Price Effect
Majors	15.3%	-0.7	-10.7%	2.0%	-8.7%	-2.8%	5.9%
R3	17.9%	-0.7	-12.5%	2.6%	-9.9%	-0.2%	10.7%
North	19.0%	-0.7	-13.3%	1.0%	-12.3%	-5.8%	6.5%
Minors	18.9%	-0.7	-13.2%	1.9%	-11.3%	-2.6%	8.7%

[60] -2.8% versus -2.3%.

The results of these computations seem inconsistent with what actually happened. For the majors, a price elasticity of 0.7 would imply that the 15.3% change in traffic would result in a traffic drop of 10.7%. The actual drop in traffic was only 2.8%. This implies that some other factor would have had to offset the decrease in traffic due to price elasticity. But during PT2 there was no such other factor, at least not one strong enough to offset the implied price elasticity effect. PT2 had traffic decreasing factors, specifically the recession as well as any potential impact of higher gasoline prices which we have not been able to model.

It is our opinion that this analysis further underscores our view that our price elasticity estimates are more consistent with actual traffic changes in PT2, than posited higher elasticities which some have claimed.

7.0 Key Findings

7.1 The challenge of forecasting BCFS traffic for PT3

It is appropriate to begin this section with a few general statements.

First, the econometric analysis used to estimate the economic model to be used forecast BCFS traffic to 2016 has weak statistical properties. While there have been some dramatic changes in the 2003-2011 period in forecast drivers, such as recession and high fuel prices, BCFS traffic was largely flat during this period, with a small net decline. It is difficult to uncover meaningful statistical relationships for a forecast model when traffic is flat, especially when driver variables have considerable variation.

Second, the stochastic forecast methodology used reveals that there is considerable uncertainty for BCFS future traffic levels. Some forecast methodologies produce a single “base case” or “central” forecast, and create the illusion that future traffic is reasonably certain. This, of course, is an illusion. There is considerable uncertainty in drivers such as GDP, with the possibility that a recession (or two) could occur between now and 2016. Other factors could act upon BCFS traffic. Some are positive, such as unexpected high tourism growth, but others are negative, such the impact of a terrorism event such as 9/11. Our methodology reveals that while BCFS traffic may grow slightly in PT3, there is almost an equal probability that it will not grow or decline.

7.2 Findings from the regression analysis

We now turn to the results of the regression analysis which formed the basis for the forecasts.

Seasonality

- BCFS traffic is highly seasonal. From a statistical point of view, almost all of the quarter by quarter variation of traffic is explained by seasonal effects.

- Expressed differently, a model which only has seasonality factors will produce a reasonably good forecast of quarterly traffic. Thus, a forecast model with a high R-square measure may merely be reflecting the ability to model seasonality but otherwise not be a good analysis of the other forecasting factors. Caution is urged.

Fare elasticity

- The demand for BCFS ferry services is price inelastic. Demand elasticities are in the range of -0.12 to -0.56.

- The demand on the Minor route group is especially inelastic, apparently being about half the elasticity of Majors.

- The demand on the North is much more elastic, likely reflecting the longer length and higher prices on many itineraries in this route group.

Traffic stimulation versus traffic shifting

- Our analysis of daily data allowed us to assess the effect of CoastSaver fare discounts. The analysis indicated that:
    - The fare elasticity found with the daily data was consistent with that with the quarterly data.
    - On average a CoastSaver discount of $4.50 increases daily traffic by 3.5%.
    - However, we observe that traffic is lower on days immediately before and after an episode of discounts. This suggests that part of the effect of discounts is traffic shifting.
    - A rough calculation suggested that a three day CoastSaver episode results in two thirds of its effect being manifested as traffic switching and one third as traffic stimulation.

GDP elasticity

- The relationship of ferry demand to real GDP was the variable with the most consistent finding. While the magnitude of the GDP elasticity varied somewhat, most models found that ferry demand varied positively directly with BC GDP. The magnitude of the effect for all but the North was less than unity, implying that ferry demand goes up and down less than swings in the economy, assuming nothing else is changing.
- For the North, the GDP elasticity estimate is greater than unity, at roughly 1.5.
- The recent economic contraction was reflected in the BCFS traffic statistics. That is, traffic fell during the recession, consistent with GDP being an important driver of the demand for ferry services.
- Our forecast models were all able to replicate the drop in traffic during 2008.

Population

- The regression analysis was unable to find any consistent effect linking traffic to population.
- This is perhaps not surprising from a mathematical sense, given that BCFS traffic on the Major and North route groups has declined since 2004 while population has grown.
- We wish to emphasis that our inability to find a meaningful statistical relationship between population growth and BCFS traffic since 2003 does not mean that population and demographic changes do not have any effect. One possibility is that there is underlying traffic growth due to population growth, but demographic shift toward an aging population may have fully offset this effect.

Gasoline Prices

- Economic theory and common sense would suggest that higher gasoline prices would decrease the demand for ferry services. As higher gas prices generally reduce highway travel one would expect this effect to reduce the demand for ferry services.

- The regression analysis was unable to find a consistent effect linking ferry traffic to gasoline prices during the period from 2003 to early 2011. This was a surprising result, and we investigated a wide range of possible models as well as simple correlation analysis. We found that there were a few cases where higher gasoline prices were correlated with lower ferry traffic, e.g., when comparing year over year October to December quarterly traffic. However, the relationship did not hold for other year over year comparison.

- It is our opinion that there likely is a long term relationship between gasoline prices and demand for ferry services. However, the statistical analysis of the post 2003 data simply is not able to reveal such a relationship. We decided to err on the side of caution, and rather than base our preferred forecasting regression on a few cases where we could find the expected relationship and ignore the other cases, we chose to exclude the gasoline price from the preferred regression.

- Hopefully repeating the analysis in a few more years time will provide more data points from which any actual gasoline price impact on ferry demand can be revealed.

7.3 Findings from the forecast

This report used a modern approach to forecasting. The traditional approach to forecasting would estimate an econometric model and then make a forecast projection with one set of assumptions on the future values of the key variables. A low and a high scenario might also be projected. However, it is rare that any of the base case, low or high projections will actually be realised.

The modern approach to forecasting has two dimensions.

- First, it recognises that there are a multiplicity of outcomes for the future. Rather than forecast one or a small number of outcomes, it is more useful to simulate a larger number of possible scenarios, and from these develop a probability distribution for the range of outcomes in any given year.

- Second, it recognises that econometric models are limited in only being able to develop estimates for demand factors that are regular in their impact. Thus, the econometric approach is useful for revealing the impact of price changes on traffic, or GDP trends. However, econometric models are unable to quantify the effect of low probability events which may have a very large impact on traffic. A terrorism event, a pandemic, a loss of confidence in air services that parallel BCFS routes, etc., all can profoundly affect BCFS traffic, but these effects cannot be estimated by an econometric model due to their low frequency of occurrence. Yet, these potential scenarios will affect the range of traffic outcomes.

The forecasting approach in this report combines a core econometric analysis of underlying effects influencing demand for ferry services with the two tenants of modern forecasting. Some of key findings from the forecast are:

- For the Minors, the 50th percentile (essentially the mean) of the 10,000 forecast scenarios that were simulated indicates that traffic is likely to decline.
  - For the Minors, the 50th percentile forecast for FY2016 is 97-98% of existing traffic.

- For the Majors, only modest growth is projected with the 50th percentile forecast.
  - The traffic index is projected to grow only from 2.460 million to 2.464 million. This is only 0.13% total growth after five years.

- There is great uncertainty regarding future ferry traffic. It is not possible to say, with a high degree of confidence, that ferry traffic will be higher by the end of PT3.

  - For the Majors, the 25/75% forecast band for FY2016 is a range from 2.41 to 2.52, which includes a 2.3% drop in traffic (and a 2.5% increase in traffic).

  - The 90/10% confidence band around the forecast ranges from 2.345 million to 2.572 million, a range that is 9% of the current level of traffic.

- The forecast risk is especially high for the Minor and North route groups.
  - The 90/10% confidence band for the North is 90% of the existing traffic level.
  - The 90/10% confidence band for the Minors is 4% of the existing traffic level.

- There are significant probabilities that there will be no traffic growth by the end of PT3.
  - For the Majors, the probability that traffic in FY2016 will be the same or less than it was at the end of FY2010 is 48%.
  - For Route 3, the probability is 23%.
  - For the Minors, the probability is 96%. This route group has significant forecast risk.
  - For the North, the probability is 36%.

It is beyond the scope of this report to comment on financial risk to BCFS. However, given that a large share of its costs are fixed,[61] it is unlikely to be able to adequately shed costs in the event of traffic reductions.

7.4 Comments on the econometric estimates

Before closing this section, we comment on the challenge of estimating econometric forecasting models for BCFS. An inspection of the quarter by quarter traffic level charts in Appendix E shows how the variation in the data is largely determined by seasonality. Indeed, a regression which only has indicator variables for the quarters will have R-square values in the high 90% range. The remaining variation in the data can only weakly estimate the regression coefficients of variables such as price and GDP, and appears unable to find any relationship with variables such as population, demographics and gas prices.[62] The small number of quarters for which data is available, and the need to control for data redefinition and regulatory changes to

[61] E.g., labour staffing on ships is fixed by regulation. The amount of capacity (sailing frequency and size of vessel) is fixed by the Coastal Ferry Services Contract. Fuel consumption is correspondingly difficult to vary, given the fixed capacity requirements.

[62] This is not to say that such variables have no long term impact on ferry traffic. We are simply saying that the existing data is not revealing such impacts.

the value of traffic and price indices, leaves few observations for meaningful statistical analysis.[63] BCFS does have earlier data available, but it is not on a consistent basis with the way the route groups are current organized.[64]

The result is that a number of the regression coefficients in the econometric traffic demand models have only modest statistical significance. In such a situation, we were guided in our choice of model where changes to the model specification do not greatly move the coefficient values. We acknowledge that the econometric regression estimates have weaker statistical properties than would be desirable. However, in our opinion, it underscores our key observation that customer demand for BCFS services may be undergoing a major transition, such as a different relationship with population and demographic trends, obscuring the ability to obtain meaningful statistical estimates with post 2003 data.

- BCFS traffic is declining on some routes and only weakly growing on others, in spite of continual population growth.
- Demographic trends such as an ageing population may explain this lackluster customer demand on the Minor route group, but the overall statistical evidence is not yet strong enough to reveal emerging relationships.
- BCFS traffic is affected by the economic cycle, but strong economic growth has not driven higher traffic volumes since 2008.
- Price increases somewhat above inflation may be a factor in slower or negative growth, but the evidence suggests that demand is relatively price inelastic. This appears to especially be the case for the Minor route group. The statistical evidence on traffic growth is not consistent with great price elasticity claims, such as -0.7.

These limitations with the econometric results underscore the value of a stochastic forecasting approach where the forecast is presented with a probability range, rather than a single set of numbers.

[63] In an attempt to increase the number of observations, data for the four route groups were “pooled” to increase the number of observations. However, this was not successful as almost every regression had incorrect signs on key variables, and magnitudes of effects which were unbelievable.

[64] Using the earlier data would necessitate developing 40 separate forecasts then making assumptions and aggregating them for each route group.

Appendix A:
Definitions and Sources of Data

Description of Variables Used in Forecast Models

Variable	Description	Source (if applicable)
Dependent Variables		
12-month rolling Quantity Index	An un-rebased index calculated by dividing the annual rolling revenue of 4 previous quarters by the direct Paasche price index. This is the index of the traffic levels of BCFS.	Calculated based on BCFS data
Pure Quantity Index	An un-rebased index calculated by dividing the actual revenue recognized in the quarter by the quarterly derived direct Paasche price index. This is the index of the traffic levels of BCFS.	Calculated based on BCFS data
Chained Dual Quantity Index (PT1,Q1 = 100)	A rebased index (100, base year) calculated by dividing the annual rolling revenue of 4 previous quarters by the direct Paasche price index. PT 1 and 2 have been chain linked together.	Calculated based on BCFS data
Pure Chained Dual Quantity Index (PT1,Q1 = 100)	A rebased index (100, base year) calculated by dividing the actual revenue recognized in the quarter by the quarterly derived direct Paasche price index. PT 1 and 2 have been chain linked together.	Calculated based on BCFS data
Passenger Traffic	Quarterly total ferry passengers by route groups	BCFS
Explanatory Variables and Instruments		
BC Population	Total quarterly BC population (Q1 1980-Q1 2011)	Statistics Canada, Cansim. Prepared by: Population Section, BC Stats, April 2011
Sunshine Coast Population	Total annual Sunshine Coast population (1996-2010)	Demographic Analysis Section, BC Stats, January 2011
BC real GDP	Real BC GDP, expenditure based in Millions of chained 2002$ (1981-2009). 2010 projected using three years simple moving average of growth rates (2007-2009). Quarterly disaggregated using real national GDP.	Statistics Canada, Provincial and Territorial Economic Accounts: Data Tables, catalogue number 13-018-X.
Gas Price Vancouver	Monthly regular unleaded gasoline at self service filling stations for Vancouver (in cents per litre). Quarterly data aggregated using 3-month averages.	Statistics Canada. Table 326-0009 - Average retail prices for gasoline and fuel oil, by urban centre
Cost of Fuel Surcharge	The fuel surcharge (rebate) is the amount of money charged (or rebated) to the passenger based upon the current price of fuel relative to threshold price of fuel.	Calculated based on BCFS data
Percentage of Fuel Surcharge	The percentage of fuel surcharge to the total revenue across a given route.	Calculated based on BCFS data
Price Cap Index	This is the index which is established by the	Calculated based on BCFSdata

Variable	Description	Source (if applicable)
	Commissioner, to set a maximum by which BCFS can increase its prices in a given quarter.	
12-month rolling Price Index	This is the index of the actual prices (or yields) charged by BCFS, using the values of traffic and revenue in the 4 previous quarters.	Calculated based on BCFS data
Pure Price Index	This is the index of the actual prices (or yields) charged by BCFS, using the values of traffic and revenue in the current quarter.	Calculated based on BCFSdata
US Visitors to BC	Total monthly overnight US visitor to BC. Quarterly data aggregated using 3-month averages.	Statistics Canada. Table: Overnight Customs Entries to BC and Canada; Prepared by Tourism British Columbia
Time Trend	Trend variable capturing the trend of time. Takes a value of 1 for the first observations, 2 for the second observation, etc.	
Indicator Variables		
Annual Indicators: D_2004FY D_2005FY D_2006FY D_2007FY D_2008FY D_2009FY D_2010FY D_2011FY	Take the value of 1 if the corresponding fiscal year applies, otherwise it takes the value of 0. The base year is fiscal year 2011.	
Quarterly Indicators: D_Q1FY D_Q2FY D_Q3FY D_Q4FY	Take the value of 1 if the corresponding fiscal quarter applies, otherwise it takes the value of 0. The base quarter is the fourth quarter.	
D-PT2	Take the value of 1 if observation is in PT 2, otherwise it takes the value of 0 (if observation is in PT 1).	
Route Group Indicators: D_Majors D_Minors D_North D_Route3	Take the value of 1 if the corresponding route group applies, otherwise it takes the value of 0. The base route group is the major route group.	
D_SARS	Take the value of 1 if observation is from FY2004 Q1, otherwise it takes the value of 0.	
D_Olympics	Take the value of 1 if observation is from FY2010 Q4,	

Variable	Description	Source (if applicable)
	otherwise it takes the value of 0.	
D_Workstop	Take the value of 1 if observation is from FY2004 Q3, otherwise it takes the value of 0.	
D_Queen of North	Take the value of 1 if observation is from FY2007 Q1 to Q4, otherwise it takes the value of 0 (only used for regression models for route group North).	
D_Bus	Take the value of 1 if observation is from FY2004 Q1 to FY2007 Q2, otherwise it takes the value of 0.	

The natural logarithms were used for the dependent, explanatory and instrumental variables in the regression analysis. Forecasts computed predicted values of the logarithm of traffic and converted these back to natural units.

Appendix B:
Correlations of Traffic Categories for Major Route Group

Correlation Matrix various BCFS Traffic Types for Major Routes

Yields

	Senior	Adult	Child	Infant	Passenger vehicles	Overheight Vehicles	Bus	Truck	Semi
Senior	1								
Adult	.962(**)	1							
Child	.940(**)	.990(**)	1						
Infant	-0.325	-0.205	-0.242	1					
Passenger	.961(**)	.999(**)	.987(**)	-0.203	1				
Passenger_Vehicle	.864(**)	.891(**)	.855(**)	-0.108	.880(**)	1			
Bus	.906(**)	.955(**)	.926(**)	-0.051	.959(**)	.916(**)	1		
Truck	.976(**)	.992(**)	.985(**)	-0.262	.991(**)	.881(**)	.936(**)	1	
Semi	.978(**)	.988(**)	.980(**)	-0.283	.989(**)	.861(**)	.933(**)	.998(**)	1

**. Correlation is significant at the 0.01 level (2-tailed).

Traffic

	Senior	Adult	Child	Infant	Passenger vehicles	Overheight Vehicles	Bus	Truck	Semi
Senior	1								
Adult	.914(**)	1							
Child	.805(**)	.963(**)	1						
Infant	.911(**)	.983(**)	.969(**)	1					
Passenger	.931(**)	.996(**)	.951(**)	.984(**)	1				
Passenger_Vehicle	.913(**)	.988(**)	.971(**)	.989(**)	.985(**)	1			
Bus	.761(**)	.907(**)	.851(**)	.822(**)	.888(**)	.856(**)	1		
Truck	.731(**)	.646(**)	.497(**)	.586(**)	.669(**)	.609(**)	.633(**)	1	
Semi	.376(*)	.606(**)	.592(**)	.494(**)	.587(**)	.540(**)	.821(**)	.462(*)	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

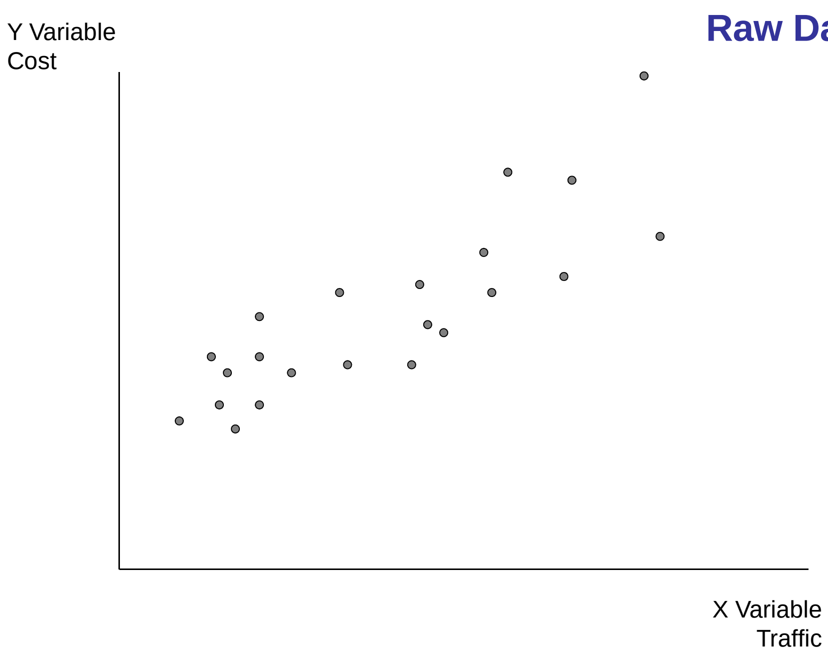
Appendix C:
A Short Description of Regression Analysis

A short description of regression analysis

Ordinary Least Squares

Statistical regression analysis seeks to 'fit' a line to data points. Consider **Figure C-1**. It shows a scatter of points. Each point has a value for two variables. In this hypothetical case (the data is made up for this example) the Y data element might be something such as cost, while the X variable might be a variable such as the level of traffic. The data in the figure suggest that cost is higher when traffic is higher.

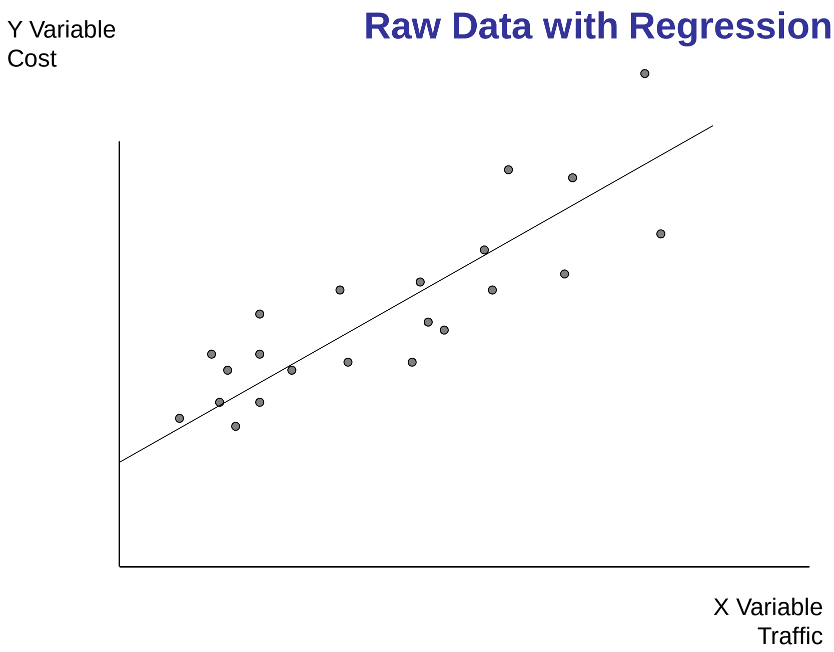
Figure C-1:
Data on Cost and Traffic



Regression analysis involves seeking a line which best 'fits' the data.[65] **Figure C-2** shows a regression line fitted to this hypothetical data. The line is displayed graphically and the regression equation is also shown on the chart. The equation says that Cost is $49.47, plus $1.49 for each additional passenger. The $49.47 million is referred to as the *constant* (or *intercept*) and the *$1.49* is the slope coefficient.

[65] There are many different lines that could be fit to the data. *Least Squares* regression analysis is one such method to fit a line. It is the method which has many desirable properties and is widely accepted in the field of economics (and many other disciplines). Least squares chooses the line that minimises the sum of the squared distances between each point and 'fitted' line. It turns out that fitting a line to minimise the sum of (un-squared) distances has some very undesirable properties. For example, the method of least absolute deviations may have multiple solutions, with no basis for choosing one versus another.

Figure C-2:
Data on cost and traffic
With Regression Line
Hypothetical Data



The above description of regression analysis is for a pair of variables: the dependent variable (the Y-axis variable, cost) and a single independent variable (the X axis variable, passenger traffic in this case). Regression analysis can also be constructed when there are multiple independent variables. This is not easy to show diagrammatically, but the concepts are the same. Regressions are typically shown via the resulting regression equation. The regression coefficients for a given X variable show the effect on the Y variable of different values of that X variable. For example, (again hypothetical)

Cost = $49.47 million + $1.49*traffic

This equation shows how cost is increased by a higher level of traffic.

Regression analysis can be conducted for any set of data. It is a mathematical exercise. Econometricians perform a reality check on the results by asking whether the resulting regression actually explains much of the differences between data points on cost (also known at the variance between cost data points) in terms of traffic level. This is referred to as checking the goodness of fit of a regression. The measure for this is referred as an R-squared value. An R^2 which is unity indicates the case where the regression explains all of the variation between airports. High R^2 values are desired, of course. Models using macro economic time series data typically achieve high R^2 values. As a general rule, models using cross section data on consumers or firms, achieve somewhat lower R^2 values. This is because there are many unique drivers of consumer and firm decisions, and models cannot include all possible influences.

Two Stage Least Squares (2SLS)

When estimating demand and supply equations, a problem arises in that price and quantity (traffic) are interdependent and determined simultaneously in the market. (They are endogenous variables.) The actual traffic and price outcome for a given year (or quarter) depends on both demand and supply factors. E.g., if labour costs (a supply factor) increase, the outcome will generally be that price increases. A higher price, however, will discourage some users and quantity will end up being lower. Price and quantity are referred to as interdependent or endogenous variables.

Both the demand and supply depend on their own exogenous variables. For supply, there are factors such as fuel prices, the cost of capital, etc., which play a critical role in the cost at which services can be supplied, but these variables are determined in the economy as a whole. Such factors are referred to by economists as *exogenous* variables, or *independent* variables. Some typical exogenous variables for demand and supply of transportation services are:

Demand:

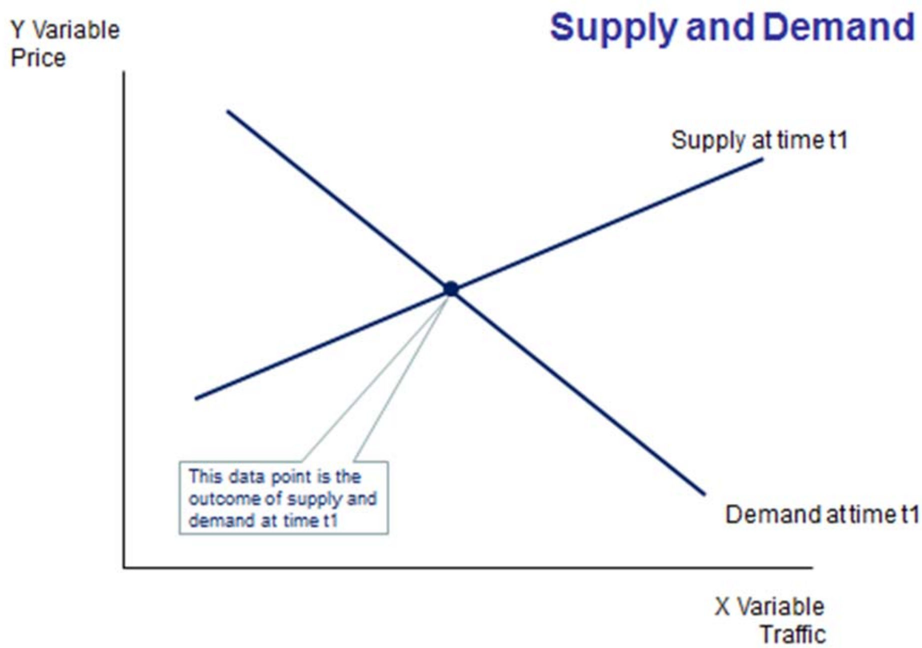
- Population/demographics
- GDP
- Seasonality (demand is higher is some seasons/quarters/months than in others
- Special events (e.g., an event such as hosting the Olympics can result in a temporary increase in demand for service.

Supply:

- Cost of providing services (labour costs, fuel costs, capital costs, insurance costs, etc.)
    - Costs can be modelled separately for each factor of production, or if an aggregate index of the company's costs is available, it can be used.
- Temporary factors (e.g., removal of vessel from service will reduce supply until the capacity is restored).
- Trend. This is usually a proxy for productivity growth, which reduces cost for any given level of traffic. Whether there is a productivity effect on supply is an empirical matter.

The previous section on OLS used an example of relating cost to traffic. That was a model where the data typically line up (e.g., as in Figure C-1) and are not affected by interaction between variables. Another way of putting this is that there is a single equation to be estimated – one which relates cost to traffic. In the case of supply and demand, however, there are two equations. One relates various variables to the level of traffic which consumers will want (consumer demand) and the other relates the level of service, costs to provide services, etc. to the corresponding price which producers will require. We call this equation the producer supply equation (or function). As is taught in the first week of most introductory economics courses, the market outcome for price and quantity (traffic) depends on both supply and demand. Mathematically there are two equations that must be solved simultaneously. Diagrammatically there are two lines or curves in the diagram. Figure C-3 shows a supply and demand curve.[66] The intersection of these curves for a given year/quarter generates a data point – that period's price and quantity.

Figure C-3:
Supply and Demand Curves



Each year/quarter/time period, there is a different set of supply and demand curves, based on that period's conditions in the market. Figure C-4 shows how three different quarters generate three data points for price and traffic. Figure C-5 shows how these points build up. This figure shows how the typical results of supply and demand interaction look like a ball of points. That is, the points do not line up along a supply or a demand curve, because they are the result of the intersection of two separate curves. Contrast this with the cost – traffic diagram in Figure C-2, where the data lined up nicely along the cost curve. In Figure C-2, OLS will produce a reasonable estimate of the cost – traffic relationship. In contrast, OLS on the data points in Figure C-5 will produce no meaningful line.

The lesson is that when attempting to estimate the parameters of a demand relationship, for example for forecasting future consumer demand for ferry services, OLS will not work. More precisely, OLS will generally produce biased coefficient estimates. It may be possible to get a computer package to produce estimates of the regression coefficients for the variables that are used, but the results will lack economic meaning. They will be statistically biased.

[66] The demand curve slopes downward (it is negatively sloped) as consumer purchase fewer units at high price and more units at low prices. Supply slopes upward (it is positively sloped) as producers need to incur higher costs to serve more traffic (e.g., additional vessel need to be purchased and labour hired.

Figure C-4:
Supply and Demand Curves for three time periods

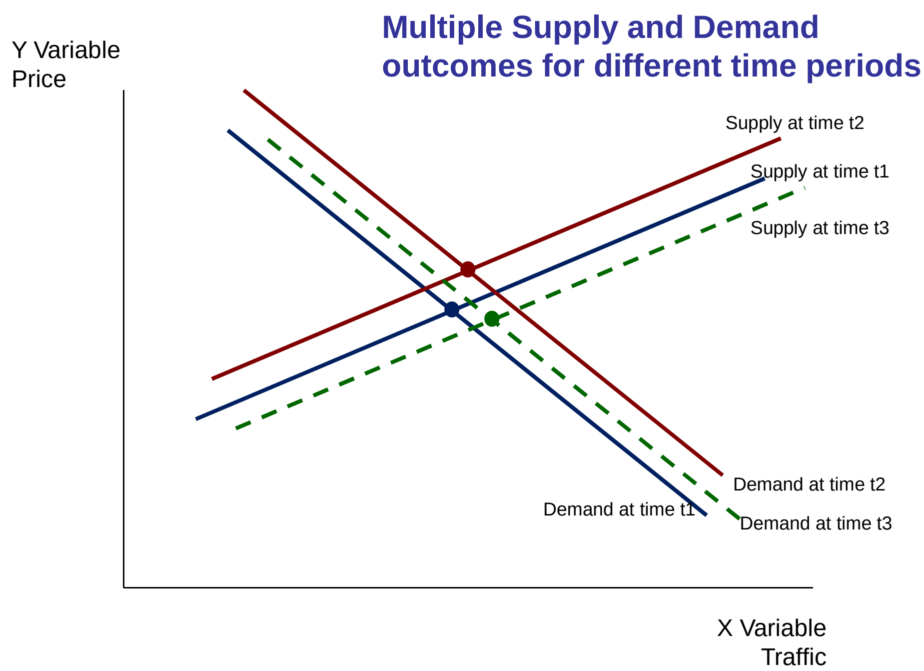
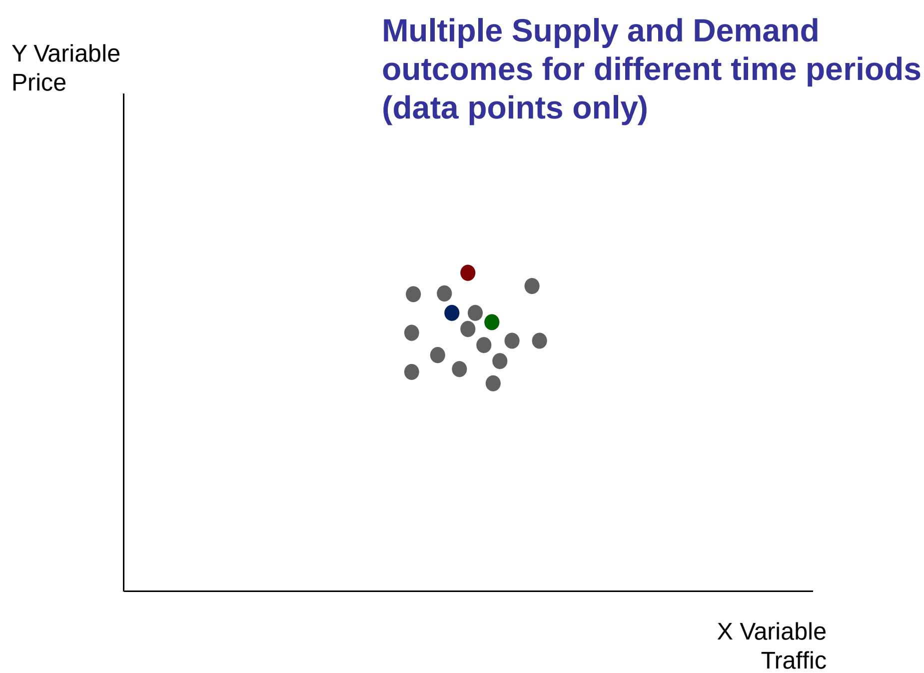


Figure C-5:
Supply and Demand data points for several time periods



Econometrics does have a solution to the problem of estimating the coefficients of a demand function. It is called two stage least squares (2SLS). While the mathematics of the routine are a bit complicated, the intuition is as follows:

- Consider the case of wanting to estimate a regression line for a demand curve. (Something similar can be done if it is the supply curve that is desired.)

- For each data point, information on one of the exogenous supply variables is used to adjust the point for the particular value of that supply factor in that time period. See **Figure C-6**.
  - For example, point A is for a low traffic level, and perhaps this was due to a supply factor, such as a ship being out of service for an overhaul. The adjustment converts the actual point to what it would have been if the supply conditions were normal.
  - Similarly point F is adjusted due to a supply factor, perhaps unusually high fuel prices, that resulted in a greater than normal cost. The adjustment converts point F to normal supply conditions.

- The first state of the 2SLS methodology converts all of the data points using the appropriate exogenous supply factors. The result is that these adjustments for supply conditions leave the differences between the points as being due only to different demand conditions in the different time periods. These adjusted points thus tend to line up along a demand a demand curve.

- The adjusted points can then be used with a regression routine and the result will be a demand curve.

Figure C-5:
Data points adjusted for exogenous supply factors

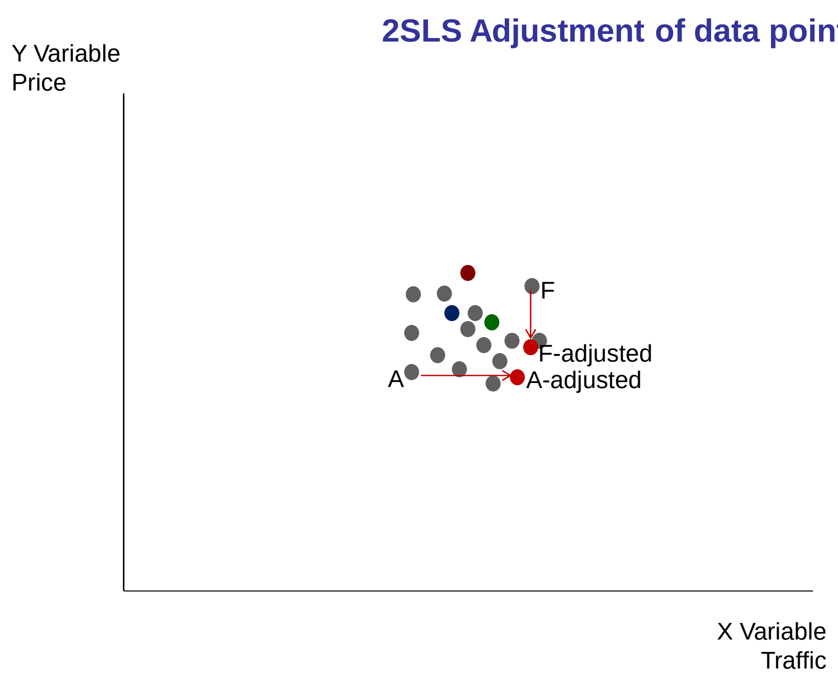


Figure C-6:
Adjusted data points

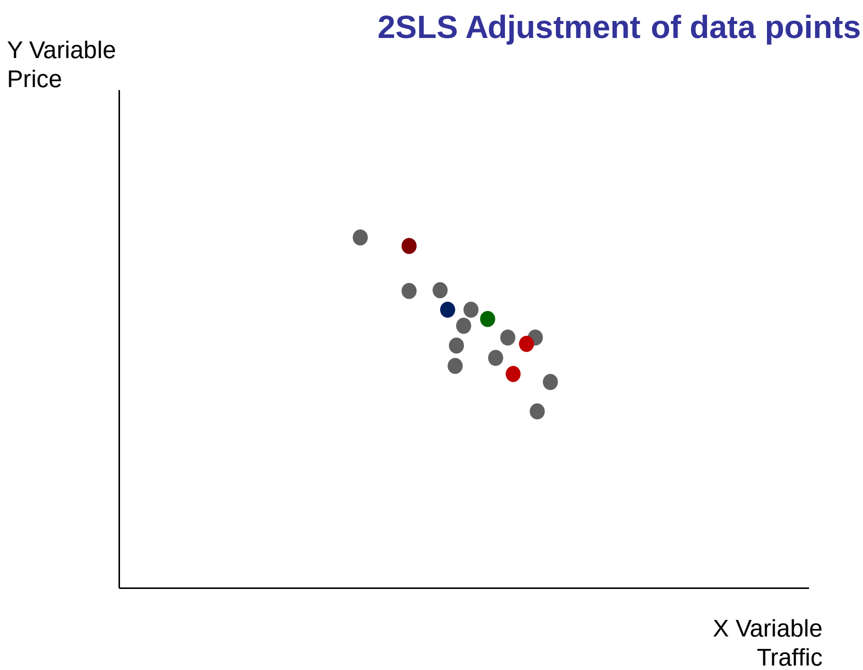
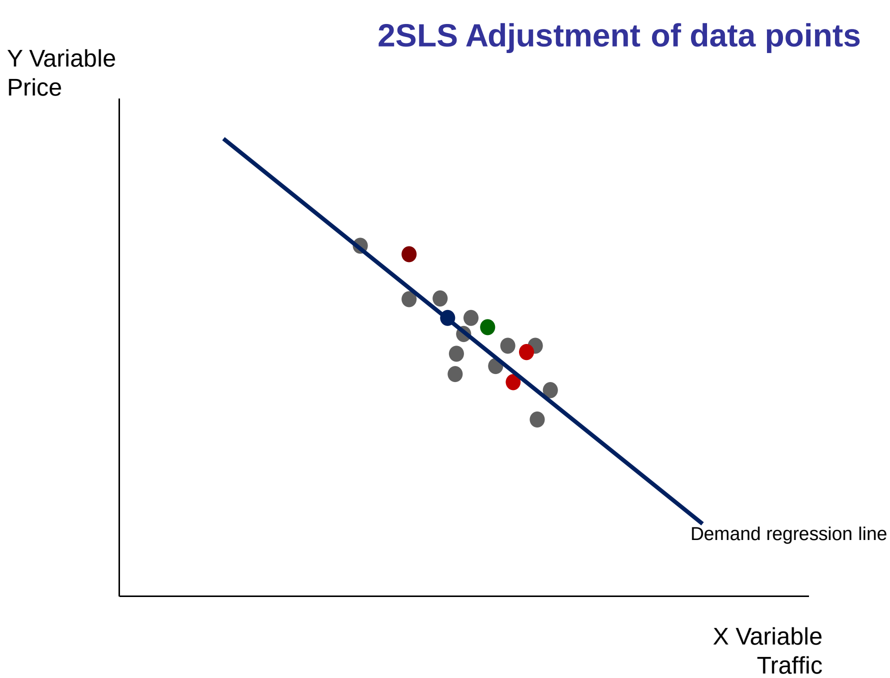


Figure C-7:
Adjusted data points with regression line



Two stage least squares can be used to produce unbiased estimates of the coefficients of a demand function (Figure C-7).[67] OLS cannot be used to estimate the demand function, as it is known to produce biased estimates in most cases.

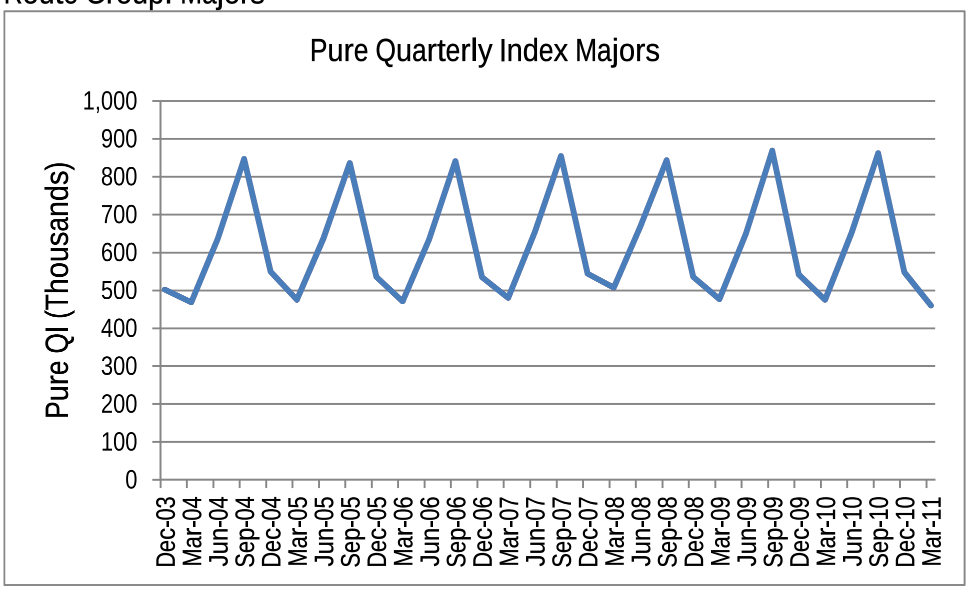
[67] There are subtleties to this, one of which is that there must be a sufficient number of exogenous supply variables.

Appendix D:
Regression Analysis of Route Group "Majors"

This appendix demonstrates our analysis of the historical traffic data for the Major route group.[68] It begins with a set of ordinary least squares (OLS) regressions. These regressions cannot contain the price variable for this route group, as doing so would result in biased coefficient estimates due to what econometricians call Simultaneous Equations bias. The analysis then proceeds to estimation with the two stage least squares (2SLS) method, which is an acceptable and widely used methodology for analysis which includes the price variable.

It is useful to begin by plotting the traffic data so that we can visually see what is to be analysed by regression analysis (**Figure D-1**).

Figure D-1
Traffic Index
Pure quarterly data
Route Group: Majors



[68] Similar analysis was performed for the other route groups but is not shown here.

Figure D-2
Traffic Index
12 month rolling traffic index
Route Group: Majors

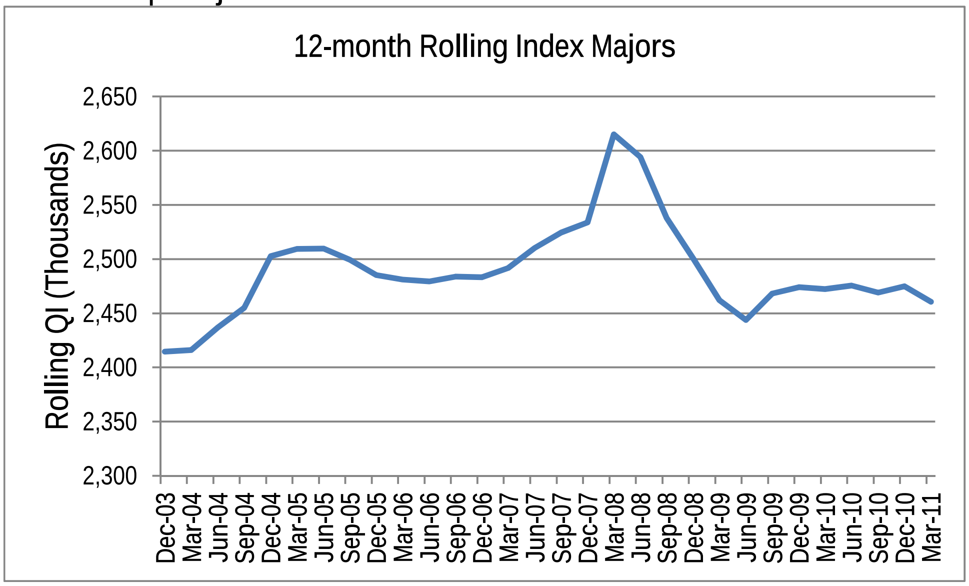


Figure D-1 shows the pure quarterly traffic index. Figure D-2 shows quarterly values for the 12 month rolling traffic index, which is the actual index used in the quarterly price compliance monitoring.

- As can be seen, the pure quarterly data have a strong, almost consistent seasonal pattern.
- The seasonality pattern is so strong that it can disguise underlying trends in the data. Hence the 12 month rolling traffic index (used in the quarterly price compliance monitoring) removes the seasonality and shows trends.
- We note that the increase in the traffic index was due in large part to redefinition of the BCFS traffic and price indexes as the end of PT1, so one must be cautious in interpreting the raw traffic data. As will be seen later, our regression analysis will correct for this data redefinition. There was also a data redefinition at the end of 2005, which accounts for part of the seeming traffic increase at that time.

Having inspected the data visually, we now turn to regression analysis.

Table D-1OLS regressions on pure quarterly data
Core underlying data indicators
Route Group: Majors

Table Major AA										
Model	Constant	Dummy Q1	Dummy Q2	Dummy Q3	Dummy PT2	Dummy Redefine	Dummy Olympic	Dummy Workshop	R-Square	Adjusted R-Square
OLS-Major AA - 1										
Coefficient	13.313									
Standard Error	0.041								n/a	n/a
T-Statistic	328.413									
OLS-Major AA - 2										
Coefficient	13.075	0.307	0.579	0.118						
Standard Error	0.008	0.012	0.012	0.012					0.99	0.99
T-Statistic	1,564.103	25.069	47.308	10.115						
OLS-Major AA - 3										
Coefficient	13.325				(0.009)	(0.027)				
Standard Error	0.081				0.103	0.122			0.00	-0.07
T-Statistic	163.972				(0.084)	(0.240)				
OLS-Major AA - 4										
Coefficient	13.325				0.012	(0.005)	(0.265)	(0.193)		
Standard Error	0.082				0.105	0.115	0.240	0.245	0.07	-0.08
T-Statistic	163.487				0.111	(0.046)	(1.104)	(0.789)		
OLS-Major AA - 5										
Coefficient	13.072	0.306	0.578	0.127	0.012	(0.005)	(0.012)	(0.067)		
Standard Error	0.009	0.010	0.010	0.010	0.009	0.010	0.021	0.021	0.99	0.99
T-Statistic	1,425.916	30.118	56.877	12.482	1.344	(0.562)	(0.571)	(3.173)		

Table D-1, above, provides the first set of simple regressions. As is standard practice in economic demand analysis, the quantitative variables (traffic, price, GDP, Population, etc.) are in natural logarithms.[69]

- Regression OLS-Major AA-1 merely regresses the quarterly traffic index on a constant.[70] The coefficient, 13.313, is the mean of the dependent variable (the log of the quarterly traffic index for this route group). If this value is exponentiated, it roughly corresponds to the mean of the quarterly traffic index, which is quarterly revenue divided by the BCFS price compliance index.

- Regression OLS-Major AA-2 adds indicator (or dummy) variables for each quarter. (The quarters are for the fiscal year. Thus Q1 corresponds to April to June.)These variables capture the seasonality in the traffic data.

[69] Economists have observed that most economic phenomena follow a logarithmic or an exponential relationship. While economists often draw demand, supply and other curves as straight lines, such linear relationships do not adequately describe actual consumer and producer behaviour. Linear demand curves, for example, imply that elasticities are constantly changing as markets grow (whereas much empirical research indicates elasticities are more constant), and that at some point, price decreases will no longer stimulate a market (or conversely, there is an upper limit on price above which no consumer will make a purchase). A logarithmic specification of a demand function is easy to estimate, as the equation is linear in the logarithms and thus easily estimated by OLS or 2SLS. As well, the coefficients in a logarithmic equation are constant elasticities, whereas a linear equation requires tedious computations to find elasticities, which are different at every different price or traffic level.

[70] Regressions with only a constant do not have R-square measures, as they are not definable in such a case.

- Because the indicators were set up to include a constant and include variables for Q1, Q2 and Q3, the constant in this regression is the log mean of the quantity index for Q4.[71]
- The Q1 coefficient rounds to 0.31 (0.012), indicating that on average, traffic is 31% higher in Q1 than in Q4.
- Similarly, the traffic index in Q2 (July to Sep) is 58% higher than Q4, on average.
- And Q3 is 12% higher than Q4, on average.
- Note that the R-squared for this regression is extremely high, 99%. This means that seasonality explains most of the variance in the pure quarterly data. This underscores a key point in our approach to forecasting. Econometric regressions with high R-squared values, by themselves, do not constitute a basis for choosing one model over another. We have found that many regressions with the BCFS data produce high R-squared values, even though the actual regression results are nonsense (e.g., population growth seeming to cause traffic declines). All regressions with the quarterly seasonality factors have high R-square values due to the strong seasonality in the traffic data.

- Regression OLS-Major AA-3 addresses the issue of major data revisions in the BCFS data. At the end of 2005, BCFS changed the definition of some of its traffic categories and this caused the traffic index to shift upward merely due to redefinition. As well, at the end of PT1, the Commission made several adjustments to the price (hence dual quantity) index. Thus the data series is influenced by the redefinitions.
  - Including indicator variables for these shifts helps to correct the regression analysis, so that shifts in the traffic index are not correlated to other variables (such as price). Failure to correct the regression for these effects could bias the coefficient estimates for the other variables.
  - While the coefficient estimates for these two indicators are not statistically significant, it is our practice to continue to include them in all regressions so as to ensure that the coefficient estimates for price, GDP, etc., are not biased.

- Regression OLS-Major AA-4 adds indicator variables to the previous regression for two special events that affected the measure of BCFS traffic. One is a work stoppage that reduced ferry traffic. The second is the potential impact of the 2010 Olympics on BCFS traffic. The Olympics can cause the demand for ferry service to temporarily shift. The work stoppage reduces capacity and thus affects the traffic measure for the quarter in which it occurred.[72] As with the data redefinition indicator variables, these will be carried forward for all regressions.[73]

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[71] If there is a constant in a regression, one of the indicator variables must be excluded. E.g., the indicator variables for all four quarters sum to a vector ones, which is the constant variable.

[72] Technical note. Generally, economists view the temporary withdrawal of capacity due to a strike, an accident or other event, as a supply effect. In diagrammatic terms, it temporarily shifts the supply curve to the left. In an unregulated market, there is no need to make adjustments in the demand curve – with reduced supply, price would rise to ration the remaining capacity. However, for a regulated firm such as BCFS, price cannot be used to ration the remaining capacity. Further, work stoppages at BCFS do not reduce capacity, they remove it completely. Thus, demand cannot be satisfied at all and the usual market mechanism will not work. Our opinion is that correct way to deal with these effects is to also put an indicator variable in the demand curve.

[73] We note that our final forecast model would have only minor changes to the coefficients if we excluded these indicators.

- Regression OLS-Major AA-5 puts together all of what we describe as the core underlying data indicators: seasonality, data redefinition and one time special events that affected traffic.

Table D-2 (On the following page) provides OLS regression outputs which individually introduce other variables: GDP, population, Vancouver gasoline prices, visitors from the US to BC, the all-in price, and a time trend.[74]

- Regression OLS-Major BB-1 adds a time trend to regression OLS-Major AA-5. The value is zero, indicating that there is essentially no trend toward higher or lower ferry traffic, after controlling for seasonality and the other underlying data indicators. This is not surprising as Figure D-2 does not reveal any obvious upward or downward trend in the data. Figure D-1 seems to hint of a tiny upward trend in the data, but the regression reveals that this is accounted for by the data indicators, specifically the PT2 data adjustment. Our analysis of more complex regression models indicates that there is no discernable underlying trend in traffic on the Majors, and when a trend variable is included, it results in wildly different values in different regression models.

- Regression OLS-Major BB-2 puts BC real GDP into the regression. This variable is not highly statistically significant.

- Regression OLS-Major BB-3 puts BC population in the regression. This result is small, statistically insignificant, and negative. It hints at a relationship where population *growth* of 10% would result in a *decline* in traffic of 0.3%. This result seems implausible. We conducted a large number of alternative specifications for the regression model and in no cases were we able to detect a plausible relationship between population and BCFS traffic. If such a relationship existed in the past, it appears to be no longer present in our data which runs from 2003 to 2010.

- Regression OLS-Major BB-4 puts the pure all-in quarterly price index to the model. We note that because this is an OLS regression, this model is biased and will not correctly reveal the effect of price on BCFS traffic. Nevertheless, we undertake the regression to investigate the correlation between traffic and price (such correlation could be due to supply factors as well as demand factors). The result is negative (-0.190).

- Regression OLS-Major BB-5 uses the price of gasoline in the Vancouver area (this price is readily obtained and it is likely that prices in other regions broadly move together. Paradoxically, the coefficient is positive, which would seem to suggest that higher gas prices leads to more traffic. We expect the opposite.

[74] The all-in price is a slight modification of the pure quarterly price index computed for the quarterly price compliance measure. Consumer demand depends on the price paid by the consumer. If the firm's accountants records some revenues in special ways, then the quarterly price index might slightly understate (or overstate) prices paid by consumers. Of special care is the way fuel surcharges are treated and discounts to seniors.

Table D-2
OLS regressions on pure quarterly data
Potential Forecast Variables, considered individually
Route Group: Majors

Table Major BB

Model	Constant	Time Trend	LN(GDP)	LN(Population)	LN(All In Price Index)	LN(Gas Price)	LN(US Visitors to BC)	Dummy Q1	Dummy Q2	Dummy Q3	Dummy PT2	Dummy Redefine	Dummy Olympic	Dummy Workshop	R-Square	Adjusted R-Square
OLS-Major BB - 1																
Coefficient	13.091	(0.002)						0.307	0.581	0.131	0.028	(0.018)	(0.007)	(0.076)		
Standard Error	0.018	0.001						0.010	0.010	0.010	0.015	0.014	0.021	0.022	1.00	0.99
T-Statistic	741.361	(1.257)						30.537	56.989	12.485	1.806	(1.301)	(0.330)	(3.449)		
OLS-Major BB-2																
Coefficient	13.183		(0.010)					0.306	0.578	0.127	0.012	(0.006)	(0.012)	(0.068)		
Standard Error	2.160		0.204					0.010	0.010	0.011	0.009	0.019	0.021	0.024	0.99	0.99
T-Statistic	6.104		(0.052)					29.345	55.556	12.091	1.289	(0.332)	(0.559)	(2.762)		
OLS-Major BB - 3																
Coefficient	13.476			(0.026)				0.306	0.578	0.127	0.012	(0.008)	(0.012)	(0.068)		
Standard Error	3.398			0.222				0.010	0.010	0.011	0.009	0.022	0.021	0.022	0.99	0.99
T-Statistic	3.966			(0.119)				29.435	55.588	11.703	1.314	(0.352)	(0.553)	(3.044)		
OLS-Major BB - 4																
Coefficient	13.950				(0.190)			0.316	0.597	0.142	0.049	(0.015)	0.008	(0.084)		
Standard Error	0.367				0.079			0.010	0.012	0.011	0.018	0.010	0.021	0.020	1.00	0.99
T-Statistic	38.038				(2.396)			31.376	49.289	12.686	2.805	(1.600)	0.376	(4.108)		
OLS-Major BB - 5																
Coefficient	13.082					(0.002)		0.307	0.579	0.127	0.012	(0.006)	(0.012)	(0.067)		
Standard Error	0.224					0.049		0.012	0.012	0.011	0.010	0.012	0.021	0.023	0.99	0.99
T-Statistic	58.466					(0.046)		25.830	48.069	12.061	1.237	(0.468)	(0.550)	(2.958)		
OLS-Major BB - 6																
Coefficient	12.868						0.015	0.298	0.562	0.127	0.014	D_Bus	(0.012)	(0.068)		
Standard Error	1.065						0.081	0.046	0.085	0.011	0.014	(0.006)	0.021	0.023	0.99	0.99
T-Statistic	12.078						0.191	6.417	6.595	11.872	0.968	0.011	(0.563)	(2.998)		

- Regression OLS-Major BB-6 puts a measure of US visitation into the regression. While only 5% of BCFS passenger traffic comprises tourist visitors, we thought it worthwhile to examine the effect of this variable, especially given that US visitors to Canada are still below the levels of 1999. The result is positive and seems to be statistically significant – a 10% decrease in US visitors would decrease BCFS traffic on the Major route group by .15%. This value seems out of proportion to the magnitude of tourism traffic in the BCFS' customer base. We conducted subsequent analysis with this variable and found that most regression have the opposite sign and thus did not consider it any further.

We now turn to Table D-3, which conducts 2SLS regression with the variables.

- The price coefficient is of the correct sign. It is statistical significant, with a magnitude of roughly -0.28.

- The GDP effect is negative without accounting for price effects but less than unity. This coefficient suggests a 10% increase in GDP decreases traffic demand by roughly 0.1%. The GDP is not statistically significant.

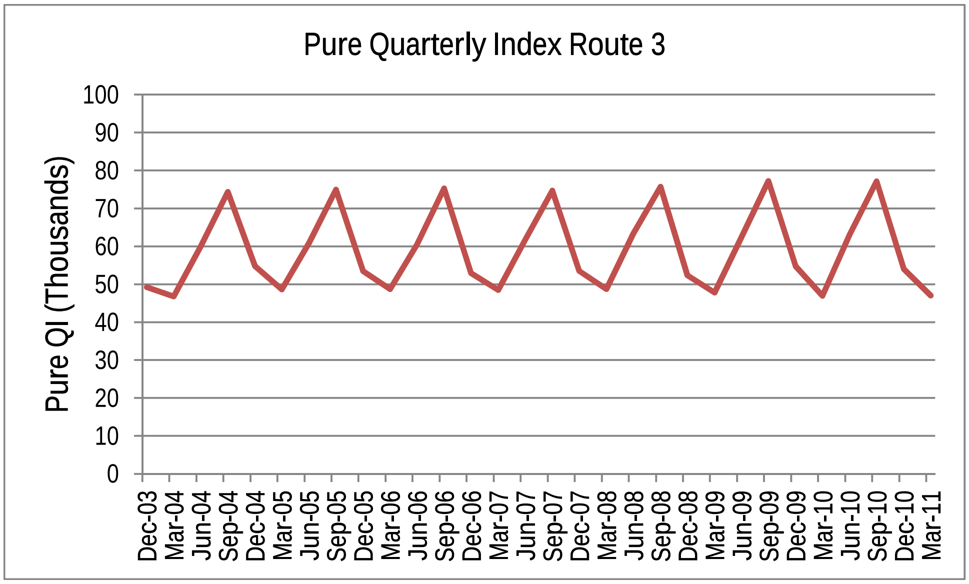
- Regression Major CC-3 is our preferred regression model. When controlling for price, the GDP variable takes the sign that is consistent with economic theory.

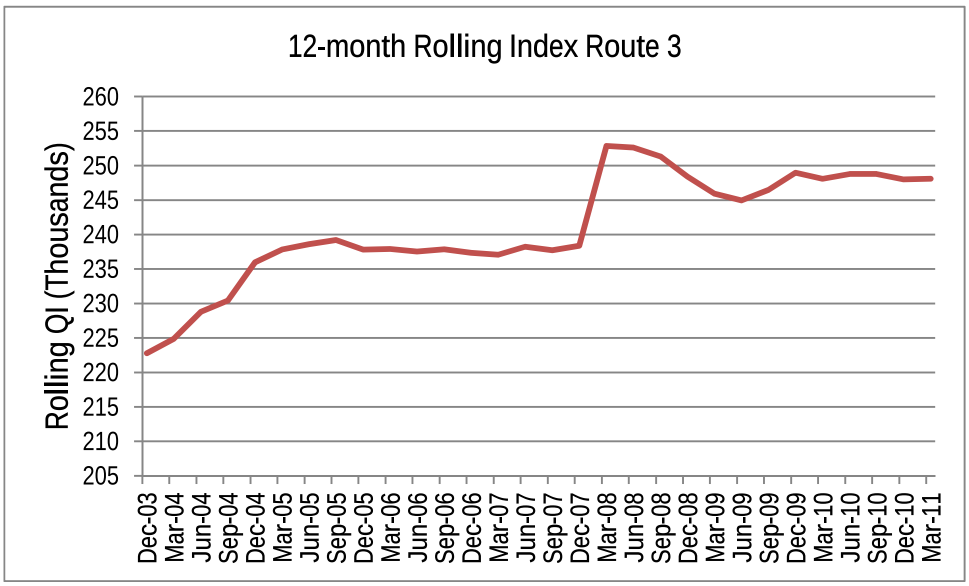
Table D-3
2SLS regressions on pure quarterly data
Route Group: Majors

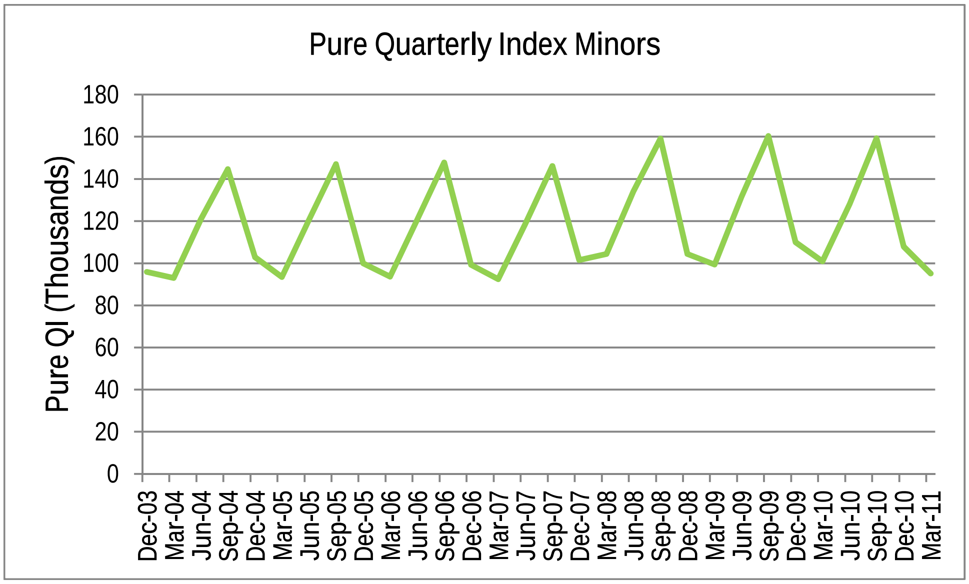
Table Major CC

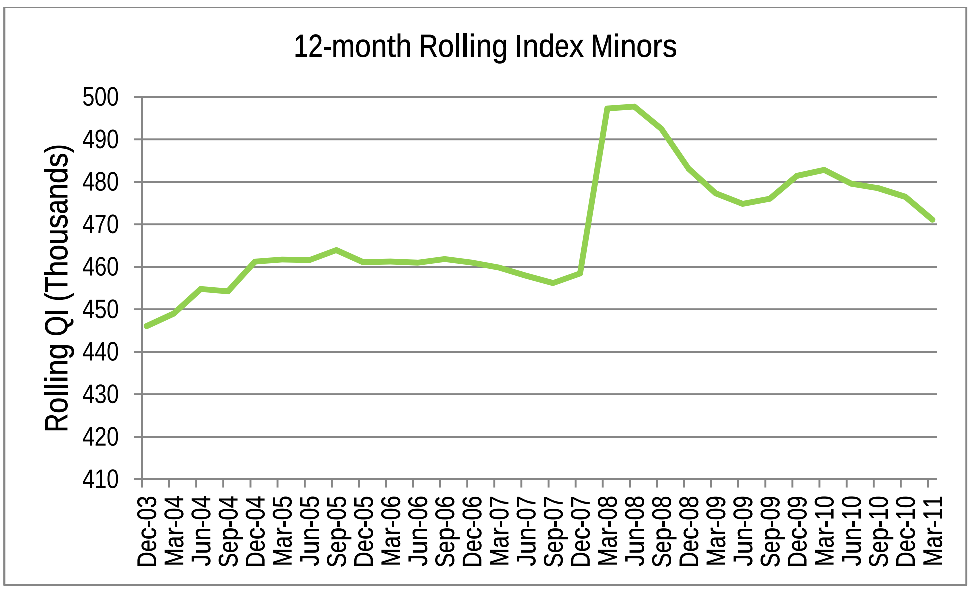
Model	Constant	Ln (All in Price Index)	LN(GDP)	Dummy Q1	Dummy Q2	Dummy Q3	Dummy PT2	Dummy Redefine	Dummy Olympic	Dummy Workshop	R-Square	Adjusted R-Square
2SLS-Major CC - 1												
Coefficient	14.344	(0.274)		0.320	0.606	0.149	0.066	(0.020)	0.016	(0.091)		
Standard Error	0.561	0.121		0.011	0.015	0.014	0.025	0.011	0.023	0.022	1.00	0.99
T-Statistic	25.567	(2.267)		28.315	39.571	10.967	2.609	(1.814)	0.716	(4.076)		
2SLS-Major CC - 2												
Coefficient	13.183		(0.010)	0.306	0.578	0.127	0.012	(0.006)	(0.012)	(0.068)		
Standard Error	2.160		0.204	0.010	0.010	0.011	0.009	0.019	0.021	0.024	0.99	0.99
T-Statistic	6.104		(0.052)	29.345	55.556	12.091	1.289	(0.332)	(0.559)	(2.762)		
2SLS-Major CC - 3												
Coefficient	12.169	(0.279)	0.207	0.321	0.606	0.148	0.065	(0.004)	0.020	(0.080)		
Standard Error	2.017	0.131	0.211	0.012	0.016	0.014	0.026	0.017	0.025	0.023	1.00	0.99
T-Statistic	6.034	(2.126)	0.980	27.174	37.895	10.796	2.465	(0.234)	0.813	(3.484)		

Appendix E:
Plots of Historical Traffic Data on Route Groups


Pure Quarterly Index Route 3
Pure QI (Thousands)
100
90
80
70
60
50
40
30
20
10
0
Dec-03
Mar-04
Jun-04
Sep-04
Dec-04
Mar-05
Jun-05
Sep-05
Dec-05
Mar-06
Jun-06
Sep-06
Dec-06
Mar-07
Jun-07
Sep-07
Dec-07
Mar-08
Jun-08
Sep-08
Dec-08
Mar-09
Jun-09
Sep-09
Dec-09
Mar-10
Jun-10
Sep-10
Dec-10
Mar-11


12-month Rolling Index Route 3
Rolling QI (Thousands)
260
255
250
245
240
235
230
225
220
215
210
205
Dec-03
Mar-04
Jun-04
Sep-04
Dec-04
Mar-05
Jun-05
Sep-05
Dec-05
Mar-06
Jun-06
Sep-06
Dec-06
Mar-07
Jun-07
Sep-07
Dec-07
Mar-08
Jun-08
Sep-08
Dec-08
Mar-09
Jun-09
Sep-09
Dec-09
Mar-10
Jun-10
Sep-10
Dec-10
Mar-11


Pure Quarterly Index Minors
Pure QI (Thousands)
180
160
140
120
100
80
60
40
20
0
Dec-03
Mar-04
Jun-04
Sep-04
Dec-04
Mar-05
Jun-05
Sep-05
Dec-05
Mar-06
Jun-06
Sep-06
Dec-06
Mar-07
Jun-07
Sep-07
Dec-07
Mar-08
Jun-08
Sep-08
Dec-08
Mar-09
Jun-09
Sep-09
Dec-09
Mar-10
Jun-10
Sep-10
Dec-10
Mar-11


12-month Rolling Index Minors
Rolling QI (Thousands)
500
490
480
470
460
450
440
430
420
410
Dec-03
Mar-04
Jun-04
Sep-04
Dec-04
Mar-05
Jun-05
Sep-05
Dec-05
Mar-06
Jun-06
Sep-06
Dec-06
Mar-07
Jun-07
Sep-07
Dec-07
Mar-08
Jun-08
Sep-08
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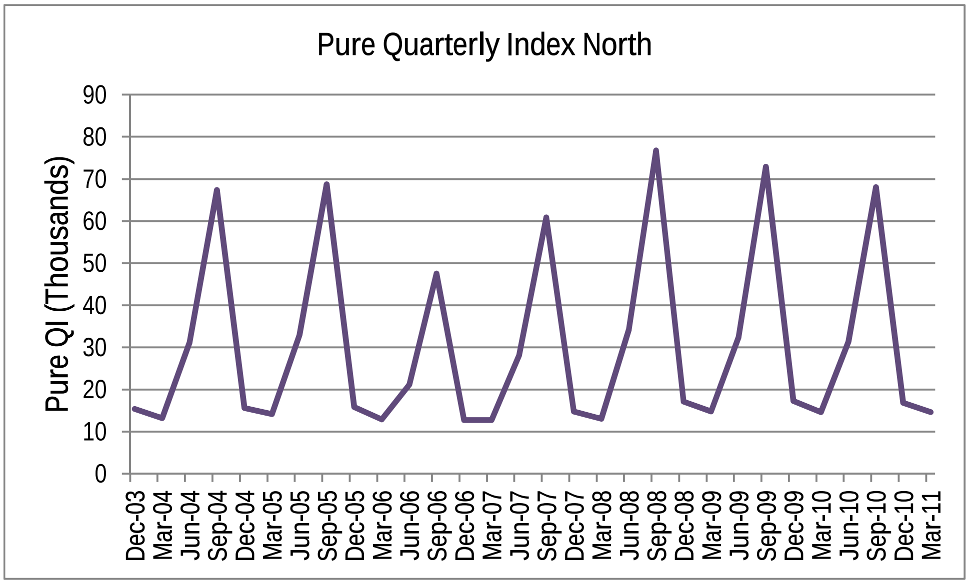
Mar-09
Jun-09
Sep-09
Dec-09
Mar-10
Jun-10
Sep-10
Dec-10
Mar-11


Pure Quarterly Index North
Pure QI (Thousands)
90
80
70
60
50
40
30
20
10
0
Dec-03
Mar-04
Jun-04
Sep-04
Dec-04
Mar-05
Jun-05
Sep-05
Dec-05
Mar-06
Jun-06
Sep-06
Dec-06
Mar-07
Jun-07
Sep-07
Dec-07
Mar-08
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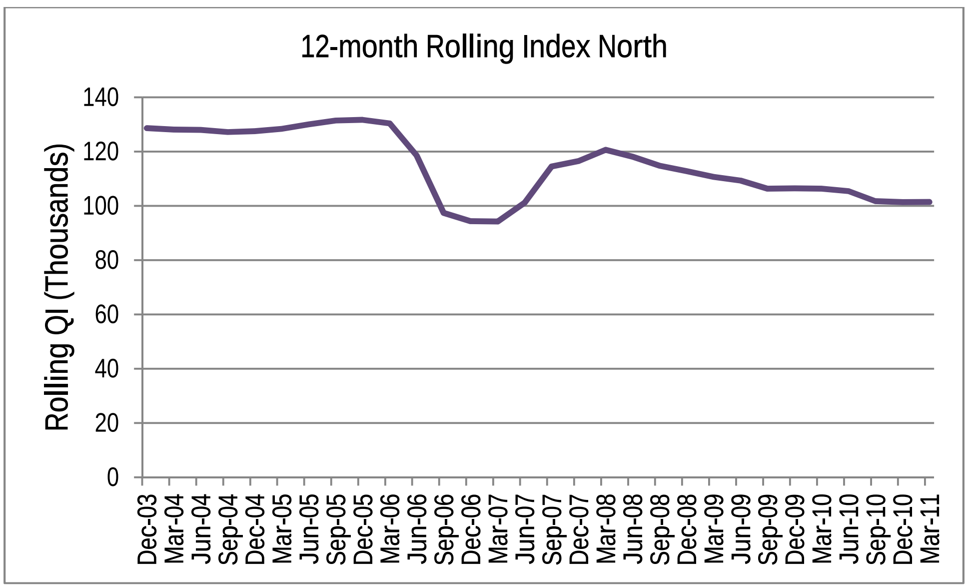
Mar-09
Jun-09
Sep-09
Dec-09
Mar-10
Jun-10
Sep-10
Dec-10
Mar-11


12-month Rolling Index North
Rolling QI (Thousands)
140
120
100
80
60
40
20
0
Dec-03
Mar-04
Jun-04
Sep-04
Dec-04
Mar-05
Jun-05
Sep-05
Dec-05
Mar-06
Jun-06
Sep-06
Dec-06
Mar-07
Jun-07
Sep-07
Dec-07
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Mar-09
Jun-09
Sep-09
Dec-09
Mar-10
Jun-10
Sep-10
Dec-10
Mar-11

Appendix F:
Traffic Forecasts by Route Group

Majors (Thousands)

	50th Percentile	25th / 75th Percentile	10th / 90th Percentile	5th / 95th Percentile	1st / 99th Percentile
Q4 2011	448.8				
Q1 2012	456.8	452.8 / 460.6	449.2 / 464.1	447.4 / 466.2	437.9 / 470.6
Q2 2012	627.2	621.2 / 632.8	615.6 / 638.1	612.4 / 641.4	530.3 / 651.6
Q3 2012	834.9	825.8 / 843.4	816.8 / 851.7	811.9 / 857.2	708.7 / 875.2
Q4 2012	529.5	523.6 / 535.0	517.4 / 540.4	513.6 / 543.9	408.6 / 563.5
Q1 2013	457.8	451.5 / 463.8	444.5 / 469.6	440.0 / 473.3	349.1 / 493.1
Q2 2013	630.4	621.5 / 639.0	611.9 / 647.1	604.6 / 652.2	517.7 / 667.0
Q3 2013	838.2	825.6 / 850.3	812.1 / 861.4	803.2 / 868.2	705.4 / 887.1
Q4 2013	529.2	521.2 / 537.2	511.9 / 544.2	504.4 / 548.7	404.1 / 564.2
Q1 2014	457.8	449.9 / 465.7	440.4 / 472.6	432.8 / 477.3	349.9 / 494.3
Q2 2014	631.1	620.2 / 642.1	608.0 / 651.9	599.0 / 658.4	522.9 / 677.6
Q3 2014	839.9	825.0 / 854.8	809.1 / 868.4	798.4 / 877.1	703.6 / 899.1
Q4 2014	531.0	521.4 / 540.5	510.5 / 549.3	501.7 / 555.1	402.4 / 573.6
Q1 2015	458.9	449.5 / 467.8	439.5 / 476.2	431.3 / 481.4	351.1 / 497.0
Q2 2015	632.0	619.1 / 644.3	605.7 / 655.9	597.5 / 663.5	522.2 / 685.1
Q3 2015	840.1	822.2 / 857.0	805.4 / 872.9	795.3 / 882.3	706.6 / 907.0
Q4 2015	531.5	520.0 / 542.3	508.4 / 552.5	499.9 / 558.5	408.5 / 577.5
Q1 2016	459.5	448.9 / 469.8	437.4 / 479.1	429.7 / 484.9	353.7 / 504.6
Q2 2016	632.7	618.0 / 647.2	603.1 / 659.9	594.2 / 668.2	523.0 / 688.7
Q3 2016	840.9	821.2 / 860.4	802.4 / 877.8	791.3 / 888.8	707.2 / 911.6
Q4 2016	531.7	518.9 / 544.3	506.4 / 555.5	497.5 / 562.7	406.8 / 582.8
FY2011	2,460.4				
FY2012	2,448.0	2,423.9 / 2,471.0	2,398.9 / 2,493.5	2,382.9 / 2,508.1	2,104.5 / 2,579.4
FY2013	2,454.9	2,418.3 / 2,490.1	2,376.1 / 2,521.7	2,335.9 / 2,542.3	2,086.8 / 2,605.3
FY2014	2,458.9	2,414.9 / 2,502.2	2,363.1 / 2,541.2	2,321.5 / 2,567.2	2,086.9 / 2,634.5
FY2015	2,461.3	2,409.4 / 2,510.6	2,354.5 / 2,558.0	2,317.2 / 2,584.8	2,083.8 / 2,658.7
FY2016	2,463.6	2,405.0 / 2,521.3	2,345.0 / 2,572.4	2,308.3 / 2,604.4	2,081.2 / 2,673.4

Route 3 (Thousands)

	50th Percentile	25th / 75th Percentile	10th / 90th Percentile	5th / 95th Percentile	1st / 99th Percentile
Q4 2011	248.1				
Q1 2012	252.9	248.1 / 257.6	243.9 / 261.8	241.0 / 264.4	230.1 / 270.2
Q2 2012	253.6	248.4 / 258.6	243.5 / 263.2	239.8 / 266.2	208.4 / 277.3
Q3 2012	254.7	248.8 / 260.8	243.0 / 266.1	238.7 / 270.0	206.6 / 287.2
Q4 2012	252.9	246.9 / 258.9	241.0 / 264.4	236.3 / 268.3	206.8 / 284.1
Q1 2013	254.0	246.0 / 261.6	238.2 / 268.7	232.5 / 273.5	207.6 / 289.2
Q2 2013	255.4	247.2 / 263.0	239.3 / 270.8	233.7 / 275.7	208.2 / 292.1
Q3 2013	257.4	248.9 / 266.1	240.6 / 274.2	234.6 / 279.6	208.4 / 296.0
Q4 2013	256.2	247.8 / 264.9	239.1 / 273.1	233.0 / 278.6	204.9 / 293.8
Q1 2014	257.0	247.0 / 266.9	237.0 / 276.4	230.3 / 282.5	204.0 / 297.4
Q2 2014	257.8	247.7 / 268.2	237.4 / 277.8	230.0 / 283.7	204.6 / 298.8
Q3 2014	259.7	249.0 / 270.5	238.3 / 280.6	230.9 / 286.9	206.0 / 303.5
Q4 2014	258.8	248.0 / 269.5	237.3 / 279.8	230.7 / 286.2	205.9 / 302.9
Q1 2015	259.8	248.0 / 271.5	236.8 / 283.0	228.8 / 290.3	205.7 / 308.0
Q2 2015	261.0	248.9 / 273.0	237.6 / 284.5	229.3 / 291.8	205.9 / 311.2
Q3 2015	262.6	250.3 / 275.3	238.6 / 287.5	230.7 / 294.8	207.9 / 313.0
Q4 2015	260.9	248.7 / 273.6	236.7 / 285.6	228.6 / 292.9	206.2 / 310.7
Q1 2016	261.9	248.5 / 275.5	236.2 / 288.4	227.5 / 296.6	205.2 / 313.4
Q2 2016	263.2	249.8 / 277.0	237.0 / 289.8	228.9 / 298.0	205.8 / 316.6
Q3 2016	265.4	251.3 / 279.3	238.2 / 292.9	229.5 / 301.4	208.3 / 319.2
Q4 2016	263.6	249.7 / 277.7	236.7 / 291.2	227.7 / 299.7	204.3 / 318.9
FY2011	248.1				
FY2012	252.9	246.9 / 258.9	241.0 / 264.4	236.3 / 268.3	206.8 / 284.1
FY2013	256.2	247.8 / 264.9	239.1 / 273.1	233.0 / 278.6	204.9 / 293.8
FY2014	258.8	248.0 / 269.5	237.3 / 279.8	230.7 / 286.2	205.9 / 302.9
FY2015	260.9	248.7 / 273.6	236.7 / 285.6	228.6 / 292.9	206.2 / 310.7
FY2016	263.6	249.7 / 277.7	236.7 / 291.2	227.7 / 299.7	204.3 / 318.9

North (Thousands)

	50th Percentile	25th / 75th Percentile	10th / 90th Percentile	5th / 95th Percentile	1st / 99th Percentile
Q4 2011	14.5				
Q1 2012	32.4	30.1 / 34.6	28.1 / 36.5	27.0 / 37.6	24.9 / 39.3
Q2 2012	78.9	73.6 / 84.0	68.9 / 88.5	66.2 / 91.1	61.1 / 95.5
Q3 2012	12.2	11.1 / 13.3	10.1 / 14.2	9.5 / 14.8	5.4 / 15.8
Q4 2012	10.1	9.1 / 11.0	8.2 / 11.8	7.6 / 12.3	4.4 / 13.2
Q1 2013	33.4	30.7 / 36.2	28.2 / 38.7	26.8 / 40.2	23.6 / 43.0
Q2 2013	84.5	78.0 / 91.3	72.1 / 97.4	69.0 / 101.3	62.9 / 108.1
Q3 2013	12.6	11.3 / 14.0	10.0 / 15.2	9.2 / 16.0	4.5 / 17.4
Q4 2013	10.0	8.9 / 11.2	7.8 / 12.2	7.1 / 12.9	4.0 / 14.1
Q1 2014	33.8	30.0 / 38.0	26.7 / 41.9	25.0 / 44.5	21.8 / 49.3
Q2 2014	84.1	74.9 / 93.7	67.3 / 103.1	63.3 / 108.9	56.4 / 120.1
Q3 2014	12.9	11.1 / 14.8	9.5 / 16.5	8.6 / 17.7	3.7 / 19.9
Q4 2014	10.6	9.0 / 12.2	7.7 / 13.7	6.9 / 14.7	3.8 / 16.6
Q1 2015	34.8	29.8 / 40.4	25.8 / 45.8	23.5 / 49.6	19.9 / 56.1
Q2 2015	84.3	72.9 / 96.9	63.9 / 109.7	58.7 / 118.3	50.8 / 132.6
Q3 2015	12.6	10.3 / 15.0	8.5 / 17.5	7.4 / 19.1	3.3 / 21.9
Q4 2015	10.4	8.5 / 12.5	6.9 / 14.7	5.9 / 16.1	3.0 / 18.5
Q1 2016	35.0	29.4 / 41.6	24.9 / 48.4	22.4 / 52.7	18.3 / 62.1
Q2 2016	84.3	71.7 / 99.2	61.2 / 114.7	55.7 / 124.5	46.6 / 145.3
Q3 2016	12.7	10.3 / 15.6	8.2 / 18.5	7.0 / 20.3	3.4 / 24.2
Q4 2016	10.4	8.3 / 12.9	6.6 / 15.4	5.6 / 17.0	3.2 / 20.4
FY2011	106.3				
FY2012	110.2	100.6 / 119.3	92.0 / 127.4	87.0 / 131.9	74.9 / 139.5
FY2013	117.0	105.5 / 129.0	94.9 / 139.8	88.8 / 146.3	76.0 / 158.4
FY2014	117.8	101.4 / 135.1	87.7 / 151.5	80.5 / 162.2	66.6 / 182.2
FY2015	118.4	98.1 / 141.0	81.4 / 163.9	71.9 / 178.8	56.6 / 204.9
FY2016	118.8	96.4 / 145.8	77.6 / 173.6	67.4 / 191.2	50.9 / 228.3

Minors (Thousands)

	50th Percentile	25th / 75th Percentile	10th / 90th Percentile	5th / 95th Percentile	1st / 99th Percentile
Q4 2011	91.4				
Q1 2012	93.0	92.4 / 93.5	91.8 / 93.9	91.6 / 94.1	90.7 / 94.5
Q2 2012	122.5	121.7 / 123.2	121.0 / 123.8	120.6 / 124.0	118.1 / 124.6
Q3 2012	153.1	152.0 / 154.0	151.0 / 154.6	150.5 / 155.0	136.7 / 155.7
Q4 2012	100.9	100.2 / 101.5	99.4 / 102.0	99.1 / 102.3	81.7 / 102.8
Q1 2013	93.2	92.5 / 93.8	91.7 / 94.3	91.3 / 94.6	75.1 / 95.1
Q2 2013	122.9	122.0 / 123.7	121.0 / 124.4	120.5 / 124.8	105.1 / 125.5
Q3 2013	153.1	152.0 / 154.2	150.7 / 155.1	150.0 / 155.6	132.5 / 156.5
Q4 2013	100.7	99.8 / 101.4	99.0 / 102.0	98.4 / 102.4	82.0 / 103.0
Q1 2014	92.2	91.4 / 93.0	90.5 / 93.6	90.0 / 93.9	74.6 / 94.6
Q2 2014	121.7	120.6 / 122.7	119.5 / 123.5	118.9 / 124.0	103.8 / 124.8
Q3 2014	152.0	150.7 / 153.2	149.3 / 154.3	148.6 / 154.8	133.7 / 155.9
Q4 2014	100.2	99.3 / 101.0	98.3 / 101.7	97.8 / 102.1	82.6 / 102.8
Q1 2015	91.9	91.0 / 92.7	90.1 / 93.4	89.6 / 93.8	74.5 / 94.5
Q2 2015	120.9	119.8 / 122.0	118.6 / 122.9	118.0 / 123.4	104.1 / 124.2
Q3 2015	150.8	149.4 / 152.1	147.9 / 153.3	147.2 / 153.9	133.1 / 155.1
Q4 2015	99.3	98.3 / 100.2	97.3 / 101.0	96.8 / 101.4	82.1 / 102.2
Q1 2016	91.3	90.4 / 92.2	89.5 / 92.9	88.9 / 93.3	74.3 / 94.1
Q2 2016	120.3	119.1 / 121.4	117.9 / 122.3	117.3 / 122.9	103.7 / 123.9
Q3 2016	150.0	148.5 / 151.4	147.0 / 152.6	146.3 / 153.3	134.1 / 154.5
Q4 2016	98.7	97.6 / 99.6	96.6 / 100.4	96.1 / 100.9	83.0 / 101.8
FY2011	471.1				
FY2012	469.4	466.4 / 472.2	463.2 / 474.2	461.6 / 475.3	415.8 / 477.3
FY2013	469.8	466.2 / 473.1	462.2 / 475.7	459.8 / 477.1	405.8 / 479.9
FY2014	466.0	461.8 / 469.7	457.5 / 472.8	454.7 / 474.6	401.9 / 477.8
FY2015	462.8	458.4 / 466.9	453.7 / 470.3	450.8 / 472.3	401.3 / 475.8
FY2016	460.0	455.3 / 464.4	450.9 / 468.0	448.1 / 470.3	402.1 / 474.1

Appendix G:
List of BCFS Routes and Route Groups

Route Group	Route
Majors	01 - Tsawwassen - Swartz Bay
Majors	02 - Horseshoe Bay - Nanaimo
Majors	30 - Nanaimo - Tsawwassen
Route 3	03 - Horseshoe Bay - Langdale
Minors	04 - Swartz Bay - Fulford Harbour
Minors	05 - Swartz Bay - Gulf Islands
Minors	06 - Vesuvius Bay - Crofton
Minors	07 - Saltery Bay - Earls Cove
Minors	08 - Horseshoe Bay - Snug Cove
Minors	09 - Tsawwassen - Gulf Islands
Minors	12 - Mill Bay - Brentwood
Minors	13 - Langdale - Gambier Island - Keats Island
Minors	17 - Comox - Powell River
Minors	18 - Texada Island - Powell River
Minors	19 - Gabriola Island - Nanaimo Harbour
Minors	20 - Thetis Island - Kuper Island - Chemainus
Minors	21 - Denman Island - Buckley Bay
Minors	22 - Hornby Island - Denman Island
Minors	23 - Quadra Island - Campbell River
Minors	24 - Cortes Island - Quadra Island
Minors	25 - Alert Bay - Sointula - Port Mcneill
Minors	26 - Skidegate - Alliford Bay
North	10 - Bear Cove - Bella Bella - Prince Rupert
North	11 - Prince Rupert - Skidegate
North	40 - Bear Cove - Mid-Coast

Glossary and List of Abbreviations

BCFS:	British Columbia Ferry Services
Consumer Price Index (CPI):	A measure of inflation within a given country using consumer prices of a basket of goods
Cross Price Elasticity:	The sensitivity of demand for a particular good to changes in the price of another good
Demand Elasticity:	See Price Elasticity
Dummy Variable:	See indicator variable
Fare Elasticity:	See Price Elasticity
FY:	Fiscal Year
Goodness of Fit:	A measure of the explanatory variables' ability in regression analysis to explain changes in the dependent variable. Assumes a value between 0 and 1 with 1 denoting a perfectly explained relationship, and 0 reflecting no relationship.
Income Elasticity:	The sensitivity of demand for a good to changes in income, income elasticity above one.
Indicator variable	An explanatory variable in regression analysis used to capture qualitative factors. Assumes the value of '1' when the factor is observed and '0' otherwise
Ordinary Least Squares (OLS):	A regression technique that minimizes the sum of squared residuals from the explanatory variables.
Price Elasticity:	Consumers' sensitivity to price changes for a particular good or service.
PT:	Performance Term. BCFS is currently in PT2.
Real gross domestic product (GDP):	A measure of the market value, adjusted for price changes, of final goods and services produced as a result of economic activity in a specific region.
Regression:	A statistical process of relating one or more variables with another.
R-Squared:	See Goodness of Fit
SARS:	Severe Acute Respiratory Syndrome
Two-Stage Least Squares (2SLS):	A regression technique used when certain OLS assumptions are violated.