



OREGON DEPARTMENT OF TRANSPORTATION

*Transportation Revenue Forecast Model:
Methodology Overview*

§1. Introduction

This report is a rudimentary discourse on the structure of the State Highway Fund Revenue Forecast Econometric Model (“SHFRFEM,” for short).

The focus is primarily on the empirical structure and assumptions driving the forecast model. Except for the brief discussion in Section 2 below, it eschews much of the process or mechanics of putting the forecast together. Those details, in and of themselves, could warrant an entirely separate report.

The discussion is organized as follows: The next section is directed to a brief overview of the forecast framework. Then, the focus is shifted to the empirical structure of the forecast models making up the quantities or transactions revenue forecast. This focus is segmented into its four major components or what are customarily referred to as “modules.” Section 4 covers transactions and revenues emanating out of the Drivers and Vehicles transactions administered by ODOT-DMV. Only a subset of the equations in this module, however, are highlighted in the discussion, given the very large number of DMV service transactions that are, by themselves, comparatively minor. Section 5 covers transactions and revenue from the Motor Carrier Transportation Division that administers taxes and truck fees for vehicles in excess of 26,000 pounds. Section 6 concentrates on motor fuel consumption that is taxed for use in vehicles weighing up to 26,000 pounds. These vehicles are the light duty passenger cars and light trucks/SUVs, as well as medium heavy vehicles that pay the fuel tax.

The fourth module of the revenue model – aviation fuel taxes and aircraft fees – is not specifically covered here inasmuch as it is a separate, stand-alone model done for the Oregon Department of Aviation. These revenues are not part of the State Highway Fund.

A final section (Section 7) is devoted to some considerations relating to the sources and structure of the assumptions that are assembled to generate the forecasts.

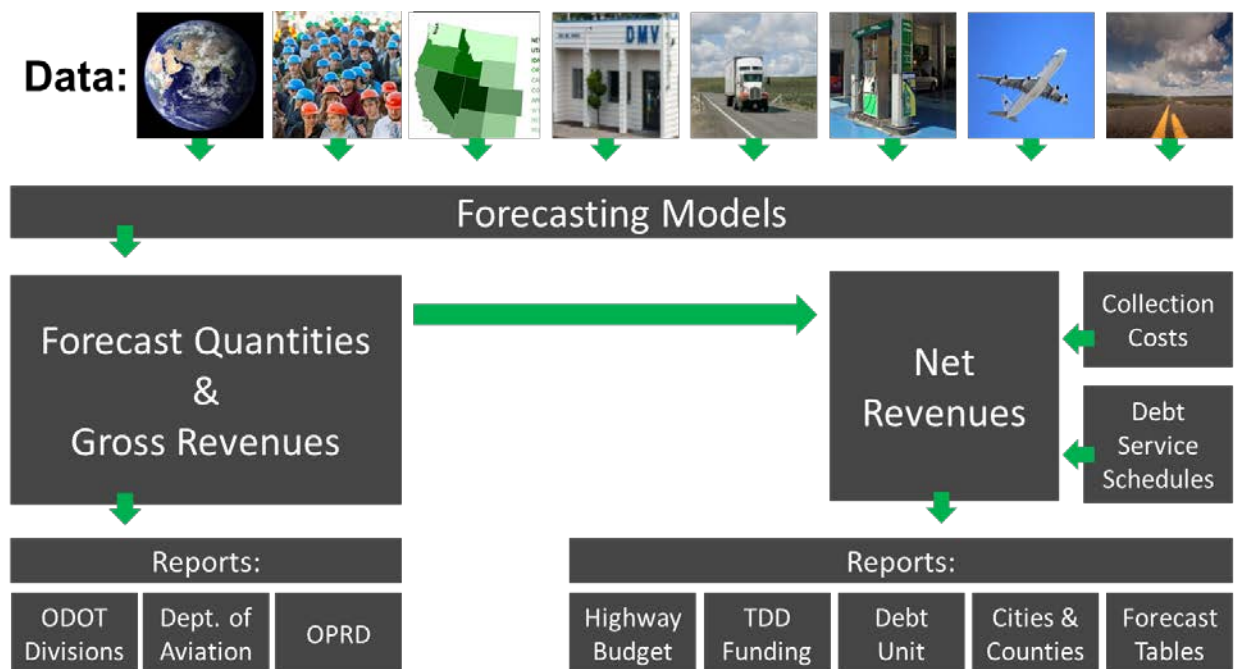
§2. Model Overview

The primary objectives for developing and regularly maintaining a detailed and somewhat complex representation of transportation revenues are three-fold. First, it drives the outlook for the revenue side of the Agency’s prospective budget for the Office of the Governor and for the State Legislature Ways and Means Committee. Second, since the model is based on actual historical data in connection with state economic and demographic data, the model is of considerable utility in assessing the incremental revenue impacts of changes in transportation tax rates and fees for legislative consideration in transportation funding initiatives. Third, maintaining and using the forecast tool on a regular basis (every six months) serves as an ongoing, early warning mechanism for revenues and economic developments to ward off any unpleasant surprises in the revenue picture that are likely to result.

A schematic of the overall forecast framework is captured in Figure 1. The revenue forecast model begins with data at a monthly frequency; maintained in the Financial Services Branch within ODOT. The time series on each quantity or transaction is tested for statistically significant seasonal factors. If present, the raw observations are seasonally adjusted. Regardless, all time series are aggregated to a quarterly frequency, since the state economic forecast and the macroeconomic forecast are at a quarterly frequency. Econometric estimation of the parameter of the equations is done for a variety of specifications for many of the key or major revenue sources, such as motor fuel consumption. Nevertheless, it is very rare to jump around from one particular specification to one of the collateral equations without particularly good justification.

After equation estimation, the models are simulated for the forecasts, conditional on the State +Economic Forecast and its associated macro outlook forecast from Global Insights (“GII”). After evaluation, the forecasts are reconstituted back into a monthly frequency for insertion into MS-Excel files for revenue simulations/forecasts. Debt service assumptions augment the revenues, since they do have an effect on apportioned net revenues from the highway fund to counties and municipalities. Net revenues are a result of netting out interagency transfers, dedicated account transfers, and selected collection and overhead costs.

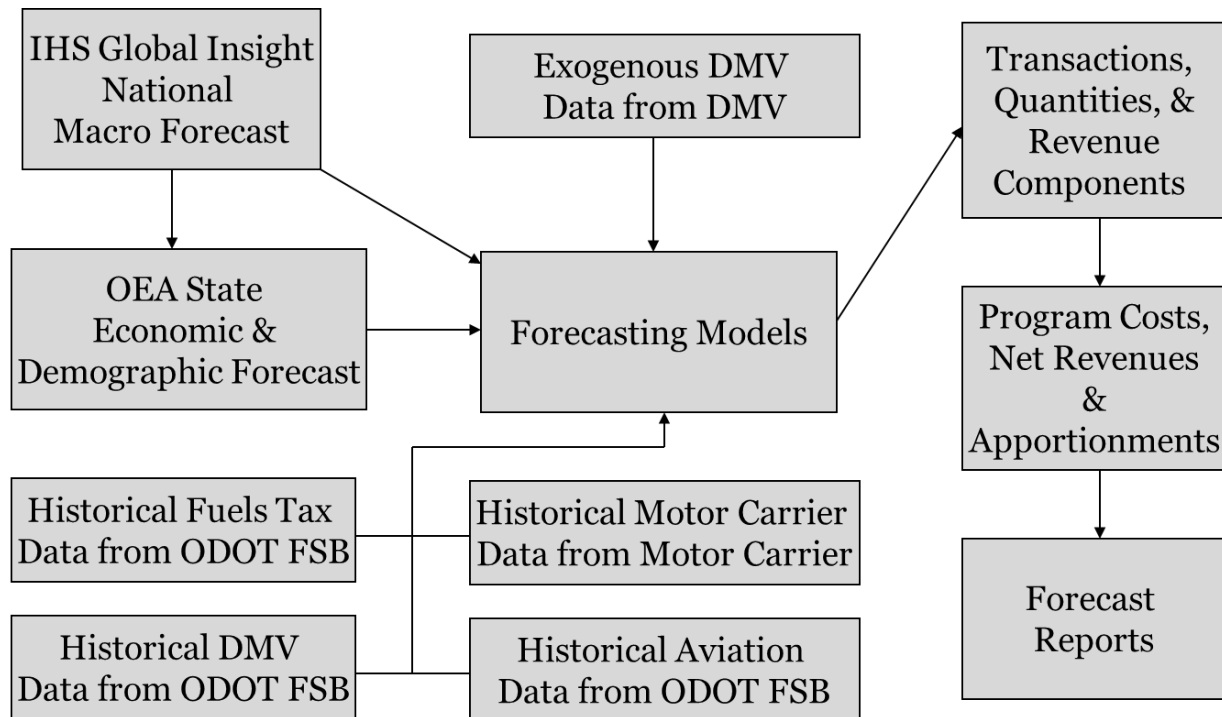
Figure 1. Schematic for the Revenue Forecast Process



§3. Structural Overview

Figure 2 is a schematic of the econometric portion of the revenue forecast model. The steps involved flow left to right in the flow diagram. In turn, Section 4 below highlights the empirically derived forecast equations for a selected set of major transaction variables for DMV. Section 5 then covers the heavy truck weight-mile tax forecasting specification. Finally, the fuel consumption model which drives the motor fuels tax revenue forecast is contained in Section 6.

Figure 2. Flow Chart of the Revenue Forecast



§4. Driver and Vehicles Module

The Oregon Department of Transportation's Driver and Motor Vehicle Division provides driver licensing, vehicle titling and registration, driver/vehicle records and vehicle dealer regulation. Driver licensing ensures people have the necessary knowledge and skills to operate motor vehicles safely on Oregon roads and highways. Vehicle titling protects ownership rights by providing evidence of ownership or a financial interest in a vehicle. Registration identifies vehicles driving on public roads and allows legal access to the highway system. The Business Regulation program licenses vehicle businesses in the state to ensure titles are correctly transferred and security interest holders are promptly paid.

DMV revenues are collected from fees charged for each of the products DMV offers. Revenues are assigned an expenditure account subjob number to be captured in ODOT's accounting system. Most

revenues have unique subjob numbers although some are grouped, such as record requests. There are roughly 220 different active DMV subjobs in ODOT's accounting system where quantities and revenues are recorded at a monthly frequency. This monthly data is extracted every six months to create a monthly time series for each subjob. The quantities, or in a few special cases, revenues, are forecast at the individual subjob level. These quantities are multiplied by the current fee to generate revenues. The individual subjob revenues are aggregated for a DMV total.

Due to the overall size of the DMV module and the different business lines within DMV, the forecast is separated into distinct submodules: Vehicle, Driver, and Business Regulation. The Vehicle submodule is the largest both in number of products forecast and revenue generated. The Vehicle submodule has revenue dedicated to the State Highway Fund as well as revenue transferred net of collection costs to other agencies and programs. Plate revenue is an illustrative example of this, where base revenue remains in the Highway Fund and the net revenue from the various group and specialty plate sales is transferred to the agencies and programs that support the mission of the plate. The Driver submodule is next in terms of size and like the Vehicle submodule has revenue dedicated to the Highway Fund and to other funds within the agency. In practice we further divide this module separating the ID Card subjobs from the rest of the Driver submodule. The rationale is that ID Card revenue is directed in statute to the Transportation Operating Fund, which is to be kept separate from the Highway Fund. Lastly, the Business Regulation submodule is the smallest and revenue generated is exclusively used to fund the Business Regulation program.

A methodological analysis of each of the DMV subjobs is beyond the scope of this summary paper. However, a walkthrough of the general forecast steps and model estimation results for one subjob is presented below along with a discussion of some overall DMV forecast issues.

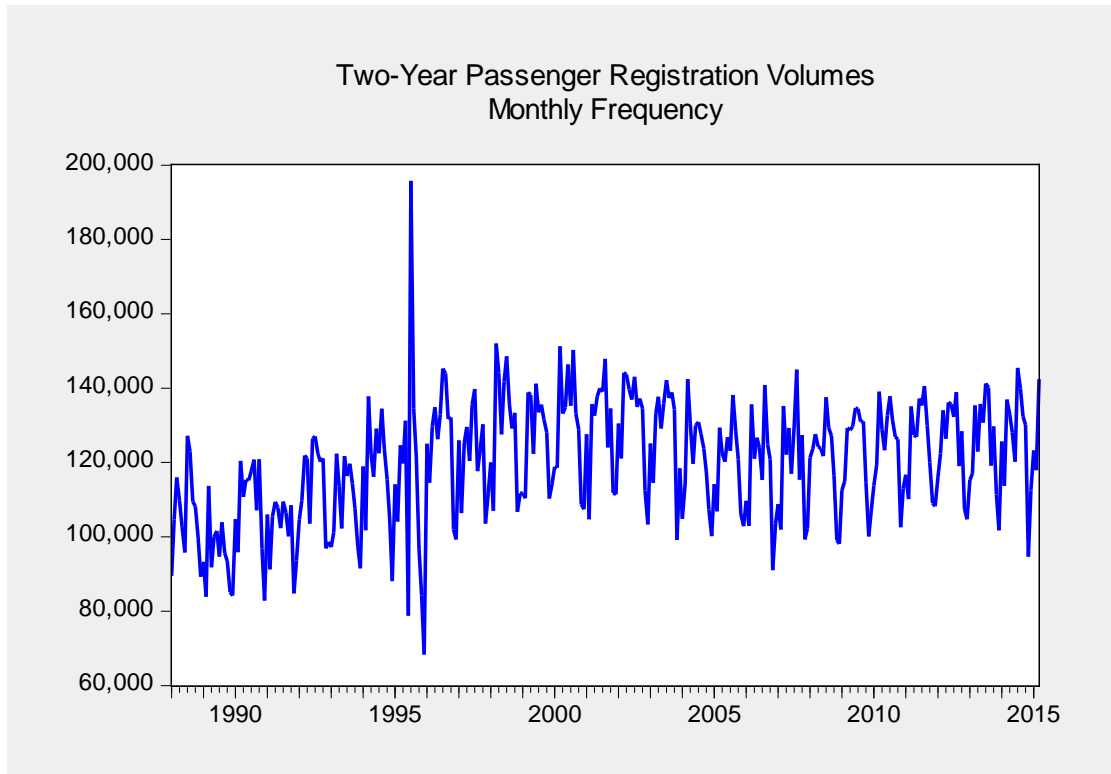
As noted above, every six months quantity and revenue data is extracted from ODOT's accounting system. This monthly data is read into the EViews econometric software program augmenting the existing time series data for each subjob. Of the 220 current subjobs only half of them have econometric or statistical models. The remaining subjobs are currently forecast using simple moving average techniques. Of the roughly 110 subjobs modeled, combinations of simple ARIMA, to more complex multivariate OLS models are used.

Of all the subjobs forecast, passenger registrations are the single largest. In Fiscal Year 2015, \$365 million in DMV revenue was forecast; \$159 Million was from passenger registrations, or 44 percent of total. Not only is it the largest but it also presents an illustrative example of the forecast process and how legislation impacts forecasting.

In the 2001 legislative session House Bill 2132 separated passenger registrations into new and used vehicle registrations, where new vehicles register for four years and used vehicles for two at the same annual fee rate. Two-year registrations represent over 90 percent of total passenger registrations and are the focus of this example. The chart below plots these two-year registrations over time.

The first step in the forecast process is to view the monthly data, test it for seasonality and identify any potential outliers. Seasonality is tested using the Census X-13 procedure. A visual inspection of the chart

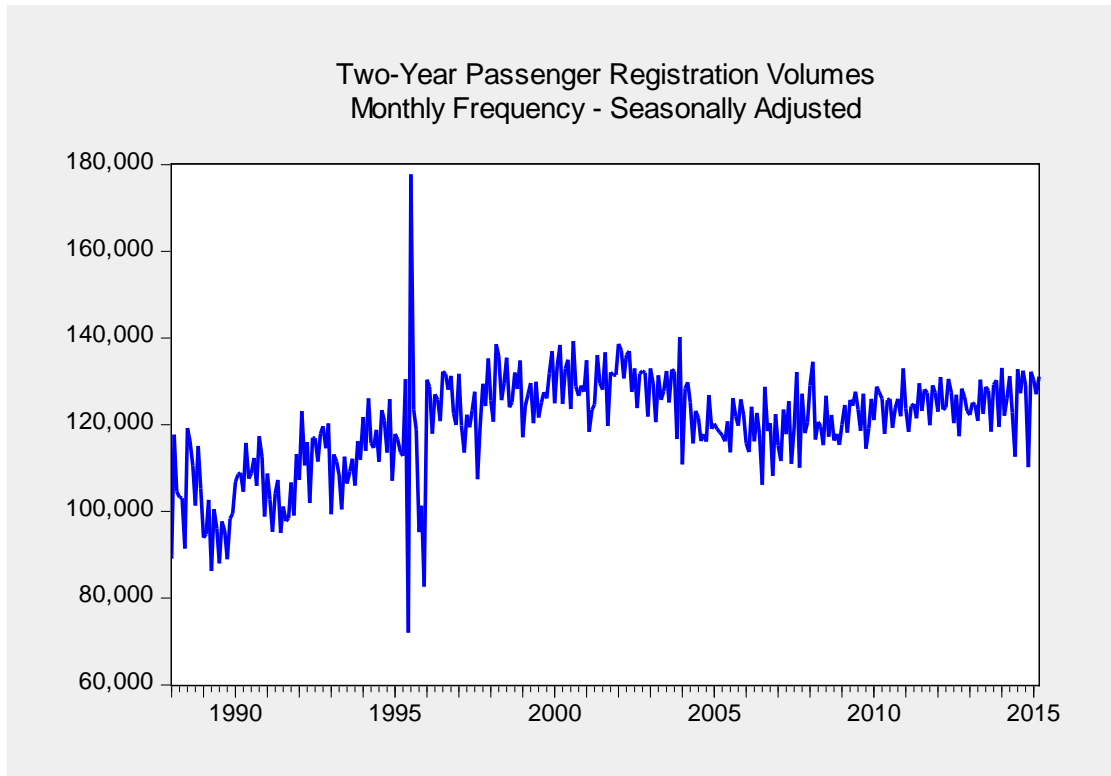
reveals the seasonal nature of the data, with the peaks in the summer months and the valleys in the winter months. It also shows a dip beginning in 2002 as new vehicles began registering for four years. This registration change was implemented in two phases with most of the state beginning in 2002 and the Portland Metro counties in 2004. Another feature is the outliers experienced in 1995. These outliers are from a computer system migration and are considered unreliable data.



After testing for seasonality and finding identifiable seasonality present in the data, the seasonally transformed series shown below is converted to a quarterly frequency for model estimation. Use of the quarterly frequency for estimation corresponds to the frequency that we receive the U.S. and Oregon forecast economic data.

The data is now smoother and shows some interesting characteristics:

1. The outliers in 1995 are even more evident.
2. The series now shows a different pattern prior to implementation of House Bill 2132. The new cyclical pattern peaks every two years matching the registration cycle. Once House Bill 2132 is implemented, the two year cycle is not easily distinguished.
3. The impact of House Bill 2132 is evidenced by the drop in registrations during the 2004 through 2007 period as vehicles that would have registered and renewed instead registered for four years.



Updating the model estimation involves first re-estimating the model over the prior forecast interval using the updated seasonally adjusted endogenous variable and updated exogenous variables. In general, a coefficient comparison between the prior forecast and this slightly updated version will change little. Any large changes should be analyzed to see if a mistake was made in the seasonal adjustment process.

The next step is to expand the sample estimation interval to include the new six months of history and then compare the results to the prior forecast. A model like the two-year passenger registration model with over 100 observations will not see much change in the coefficient values from one forecast to the next unless something radically changes with the data, which helps create a stable forecasting model. Other models with fewer observations sometimes see larger changes in coefficient values and probabilities. This can sometimes lead to variables becoming insignificant or to other variables being added. The two-year passenger registration model is estimated in the log-log functional form with the linear model:

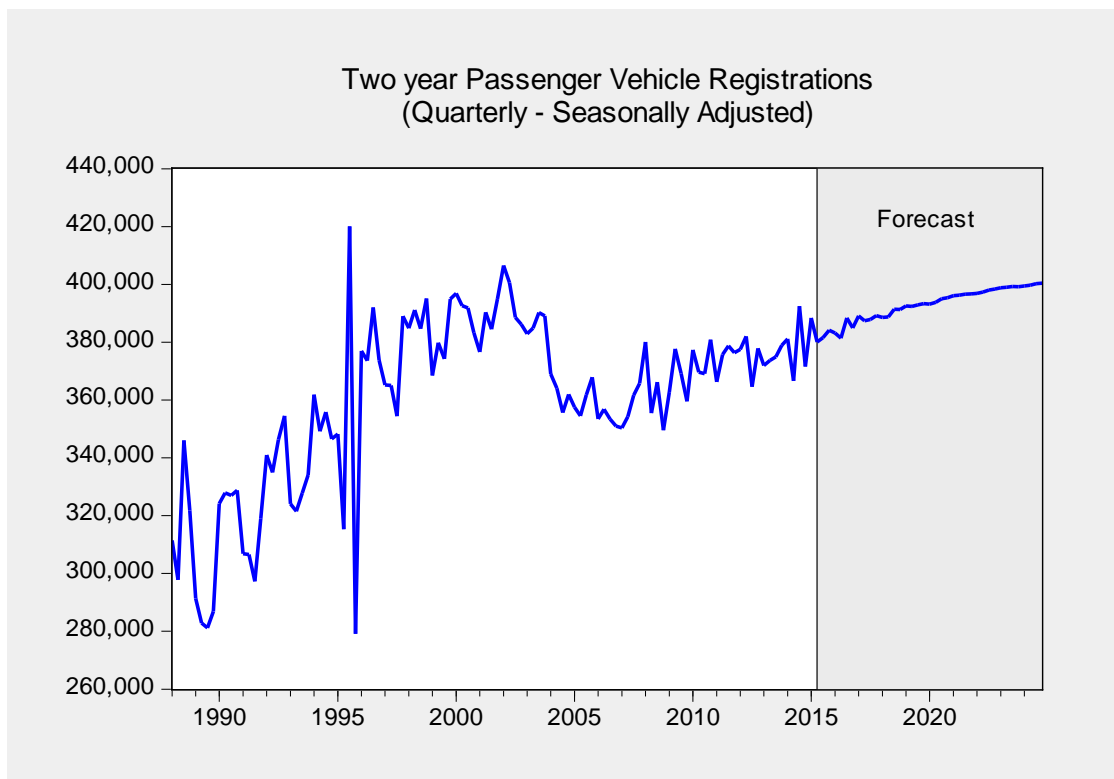
$\ln(y_t) = \beta_1 + \beta_n * \ln(x_{n(t)}) + \varepsilon_t$ where y_t is the two year passenger registration value at time period t and $x_{n(t)}$ are the exogenous variables estimated at time period t or at a time specified by their lag structure.

The fully estimated model is:

$$\ln y_t = \beta_1 + \beta_2 * \text{dummy}_{1995_2(t)} + \beta_3 * \text{dummy}_{1995_3_4(t)} + \beta_4 * \text{dummy}_{1996_3(t)} + \beta_5 * \text{dummy}_{1988(t)} + \beta_6 * \ln(\text{two_year_passenger_reg}_{(t-7)}) + \beta_7 * \ln(\text{two_year_passenger_reg}_{(t-8)}) + \beta_8 * \ln(\text{two_year_passenger_reg}_{(t-9)}) + \beta_9 * \text{dummy}_{1997(t)} + \beta_{10} * \text{strucchg}_{(t)} + \beta_{11} * \ln(\text{four_year_passenger_reg}_{(t-16)}) + \beta_{12} * \text{dummy}_{1995_2(t)} + \beta_{13} * \ln(\text{light_title_transfers}_{(t)}) + \varepsilon_t$$

Outliers identified from data quality issues are removed using the dummy variables. The strucchg variable takes a value from zero to one. It is zero prior to the first quarter of 2004, one from the first quarter of 2004 through the fourth quarter of 2005, and then declining to zero by the second quarter of 2008. This variable corrects for the change from all passenger registrations lumped into one subjob to having a separate subjob for four year registrations as discussed above.

Once the model has been estimated over the current interval the model is checked for serial autocorrelation, a common problem in time series data. If none is detected, or in other models, detected but hasn't changed, it is forecast over the specified interval. The forecast results are transformed back into the monthly frequency and seasonally unadjusted. This final product is ready for input into the variety of spreadsheets that generate reports for the agency. The chart below shows the forecast for two year passenger registrations at the quarterly frequency.



Elasticities provide an easy way to evaluate the impact of the model exogenous variables on the estimated endogenous variable. Below is a table of elasticity estimates for the applicable two-year passenger registration model variables, along with some additional model statistics.

Table 4.1 Estimated Sensitivities

Variable (x)	Elasticity (β)
Two-year passenger registrations lagged seven quarters	0.18
Two-year passenger registrations lagged eight quarters	0.46
Two-year passenger registrations lagged nine quarters	0.11
Four-year passenger registrations lagged sixteen quarters	0.003
Light vehicle title transfers	0.12
Explained Variation as a percentage	94.2%
Relative Model Error	2.1%
Estimation Interval	1988Q1 – 2015Q1
Number of Observations	109
Estimation Method	OLS

A common feature of registration models is to have the current registration period a function of the registration length, so in the two-year passenger registration model the current value is a function of the value eight quarters previously, or two years. It is noteworthy that seven and nine quarters are also significant, indicating both early and late registrants on a consistent basis. The elasticity is strongest in the eight quarter lag at 0.46, but in total the elasticity for the registration lag is 0.75. This is interpreted to mean a 10 percent increase in the number of passenger registrations two years ago yields a 7.5 percent increase in the number of two year passenger registrations in the current period.

The other registration lag included is passenger vehicles registered four years ago, which were new vehicles at that time. These are vehicles would be renewing their registration in the current period. The sixteen quarter lag of four year registrations is significant and a ten percent increase in the number of passenger registrations four years ago would yield a 0.03 percent increase in the current period. This is very small but is understandable in the context that new vehicles represent only a fraction of total registered vehicles.

Light title transfers are the final exogenous variable in the model and are defined as the DMV recorded sales of used light vehicles. This variable accounts for registrations occurring in-between the normal registration cycle from sales of used vehicles that weren't already registered. The elasticity is 0.12, so an increase in the light title transfers of 10 percent yields a 1.2 percent increase in the current period number of two year passenger registrations.

Overall, the two year passenger registration model provides a good example of the forecast process and issues involved with DMV forecasting. The challenges can be generally summed into three categories.

1. Data – unfortunately the data is not always clean due to system or accounting errors despite aggregation at the quarterly level which helps timing issues where one month might be low and the next month high. This makes the use of dummy variables common.
2. Law changes – DMV bills creating new subjobs or changing the definition of existing ones, as well as changing fee rates, can have severe model implications. In some cases this creates breakpoints in the data requiring truncation of the sample interval.

3. Econometrics – the very nature of the time series data can lead to non-stationarity of the endogenous variables, or serial autocorrelation of the model. Each of these needs to be dealt with in order for the Ordinary Least Squares estimator to be the best linear unbiased estimator.

Each DMV subjob can have its own unique set of challenges, but over time much work has and continues to be done to test and improve model specifications. In some cases, multiple competing models are estimated to ensure that the chosen model is the most accurate.

§5. Forecast Model for Weight-Mile Tax Revenues from Heavy Trucks

Generally, the relationship is expressed as (for any period or observation “t”):

$$Q_t = F(a_0, x_{1,t}, x_{2,t}, x_{3,t}, x_{4,t}, x_{5,t}, \epsilon_t),$$

where

Q_t = weight-mile revenue per one-cent of tax

a_0 = a constant intercept term,

$x_{1,t}$ = real fuel price,

$x_{2,t}$ = Oregon Employment – Construction Sector,

$x_{3,t}$ = real consumption spending on durable goods,

$x_{4,t}$ = an index of industrial production,

$x_{5,t}$ = growth rate in Oregon employment in durable goods manufacturing, lagged, and

ϵ_t = a random disturbance term, independently and identically distributed with a zero mean and a fixed, finite variance.

The functional forms specified are the traditional linear and multiplicative models. The linear or additive form possesses an advantage of sensitivities that can vary somewhat as a function of the point of evaluation. The multiplicative forms – which become linear in logs upon transformation – do not allow the elasticities to vary; they remain constant across all observation points.

Along with the customary additive and multiplicative specifications to explain the behavior of taxable fuel sales, several other statistical representations are examined and maintained from time to time. Autoregressive-Integrated-Moving Average time series models (“ARIMA”) are specified and tested to attain parsimonious forecasting equations. However, experience has routinely shown that these models are quite limited beyond 2 quarters out; a considerably more abbreviated period than the span of interest of 4 to 6 years. Another set of models belonging to the class of Vector-Auto-Regressive

equations (“VAR”). However, these are susceptible to multicollinearity in the exogenous variables such that the information statistics governing the lengths of auto-regression produce somewhat limited breadth, though less limited than in the case of ARIMA parsimonious representations.

Figure 5.1 graphs the historical observations for the weight-mile revenue component, along with the current forecast.

Figure 5.1 Weight-Mile Observations, Normalized on the Composite Tax Rate, 2000-2019

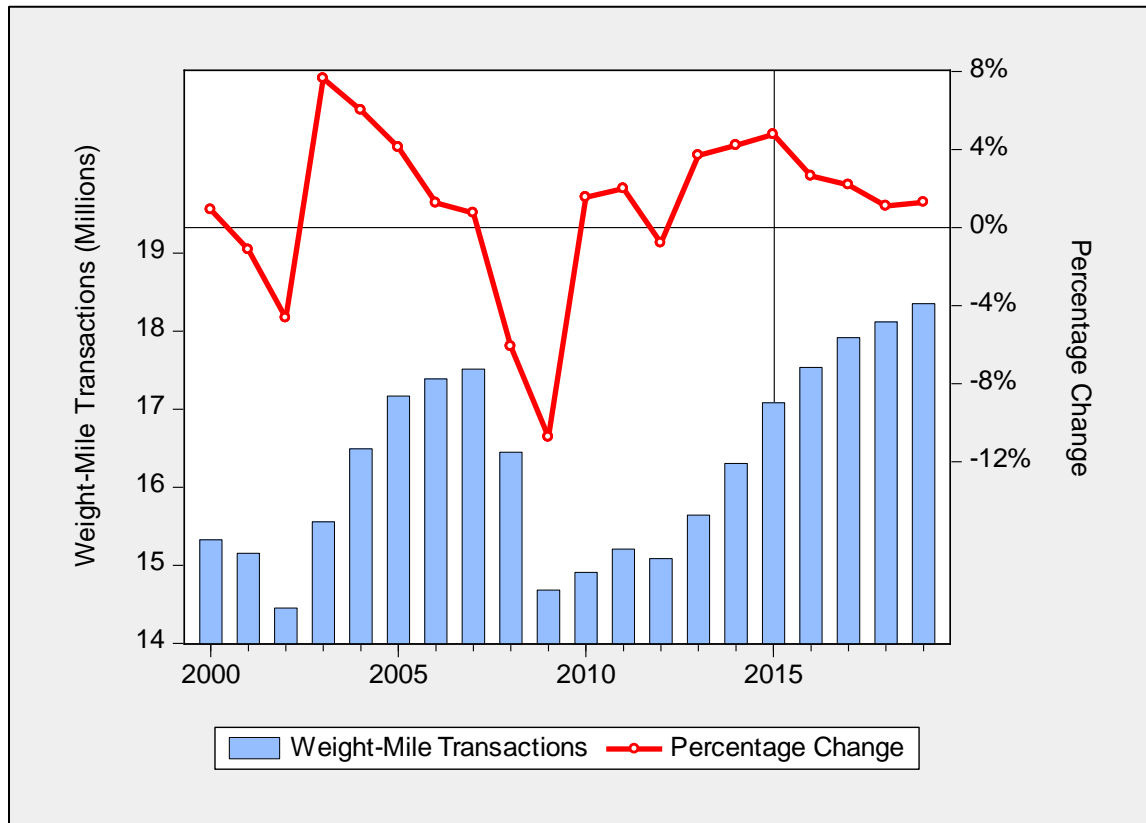


Table 5.1 Estimated Elasticities in the Weight-Mile Tax Model for Heavy Trucks

VARIABLE	Elasticity
Real Fuel Price	-0.05
Oregon Employment – Construction Industry	0.31
Real Consumption Spending on Durable Goods, nationally	0.22
An Industrial Production Index	0.031
Growth Rate in Oregon Employment in Durable Manufacturing (lagged)	0.92
Explained Variation as a %	89.3 %
Relative Model Error	2.4 %
Estimation Interval Observations	1995Q4-2015Q1 78
Estimator	OLSQ

The interpretations of the estimated sensitivities are as follows:

Fuel prices – adjusted for inflation – play a role in the weight-mile equation for heavy trucks as representing an input in the production of freight and delivery transportation services. Thus, heavy vehicle demand for fuel is a derived demand, and moreover the substitutes for diesel fuel are very few. All else equal, changes in fuel use are mirrored by changes in miles of travel. As a result, the elasticity, while statistically significant, is quite small. A 10 percent increase in diesel fuel prices only begets a 0.5 of a percent reduction in weight-miles driven, and with a lag of 2 quarters. As customarily found, derived demand for fuel tends to be inelastic, and, given the connection of fuel usage to weight-miles of travel, this insensitivity carries over to weight-miles, as well.

The pace or scale of the economy is a major driver of miles traveled by heavy vehicles. The overall pace of economic activity in the state is represented by a number of dimensions in the model. First, employment in the construction industry is a key element. More construction activity, both commercial as well as residential, generates the need for more building materials to be transported. The current point estimate of this elasticity is 0.31, indicating that a 10 percent increase in construction jobs induces a 3.1 percent increase in miles of travel by heavy trucks. Second, the level of consumer demand for durable goods drives the need for freight movement. A 10 percent increase in inflation-adjusted durable goods spending brings about a 2.2 percent in heavy truck miles driven. There are two remaining scale elements, though they are not as potent as the foregoing ones. The rate of industrial production activity is positively associated with more miles of travel in the heavy vehicle class. The sensitivity is, however, somewhat muted, and it occurs with roughly a lag of 3 quarters. A 10 percent increase in the index for industrial production generates only a 0.3 percent in vehicle miles of travel – 3 quarters later. The final economic activity factor is the growth rate in durable manufacturing jobs in Oregon. A 10 percent increase in the rate of growth (a very substantial increment beyond normal experience), would generate a 9 percent increase in heavy truck weight-miles all else equal.

§6. Forecast Model for Fuel Consumption

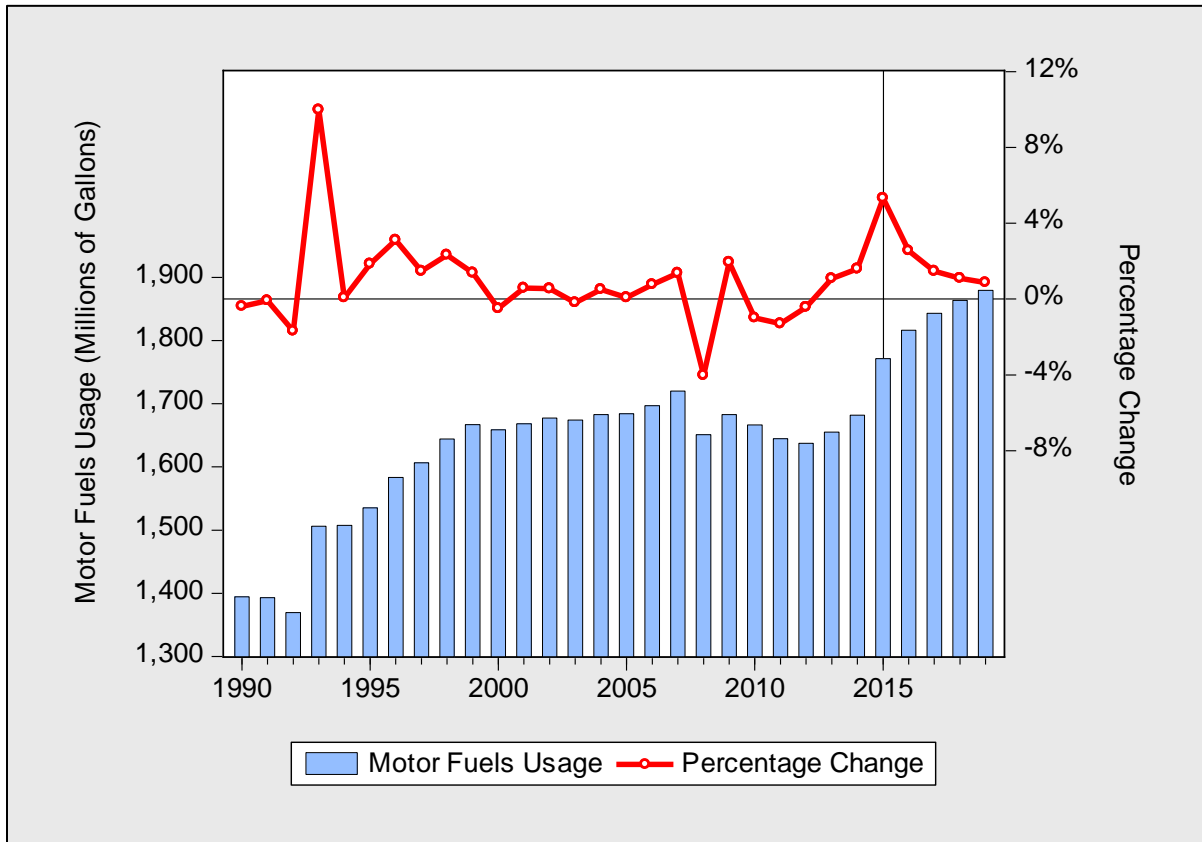
Motor fuels tax revenue represents a significant portion of State Highway Fund revenues at roughly 50 percent. The tax is collected on gasoline and diesel fuel gallons sold to drivers of vehicles weighing up to 26,000 pounds. [Vehicles that weigh more than 26,000 pounds are taxed under a weight-mile tax structure instead of a fuel tax, as was covered in the narrative above.] The current tax rate of 30 cents per gallon was implemented in 2011. Prior to that increase, the last tax rate change was in 1993 to 24 cents per gallon.

Motor fuel consumption or fuel usage falls under the nature of a “derived demand.” That is, fuel is not “consumed” for its intrinsic, utility producing elements, but rather as an intermediate input in enabling drivers to pursue or accomplish activities which do, such as commuting and recreation/leisure activities.

The specifications for fuel usage in light and medium duty vehicles are, however, not structural demand equations. Rather, they are like reduced form equations in that they are a blend of both demand and supply elements. Most significantly, fuel prices are treated as if they are exogenously determined since prices are largely determined by market conditions on the entire west coast and not within Oregon specifically. Reduced form specifications are generally acceptable for forecasting purposes, as opposed to hypothesis testing where structural equations are warranted.

A chart of annual observations for motor fuels is contained in Figure 6.1, along with a contemporaneous forecast out through 2019.

Figure 6.1 Motor Fuels, 1980-2019



Generally, the forecasting relationship is written as (for any period or observation “t”):

$$Q_t = F(a_0, x_{1,t}, x_{2,t}, x_{3,t}, x_{4,t}, x_{5,t}, x_{6,t}, \underline{D}_t, \varepsilon_t),$$

where

Q_t = gallons of fuel taxed, seasonally adjusted

a_0 = a constant intercept term,

$x_{1,t}$ = real fuel price,

$x_{2,t}$ = fuel efficiency of the light duty vehicle fleet,

$x_{3,t}$ = Oregon Total Non-Farm Employment,

$x_{4,t}$ = Oregon real personal income,

$x_{5,t}$ = consumer sentiment,

$x_{6,t}$ = Oregon Labor Force Participation Ratio scaled with Oregon total population,

D_t = binary intercept shift variable(s), and

ε_t = a random disturbance term, independently and identically distributed with a zero mean and a fixed, finite variance.

Current Parameter Estimates and Their Interpretation

Table 6.1 Estimated Elasticities in the Motor Fuels Model

VARIABLE	Elasticity
Real Fuel Price	-0.09
Oregon Total Non-Farm Employment	0.23
Oregon Real Personal Income	0.24
Fuel Efficiency	-0.16
Oregon Labor Force Participation Rate (OED)	0.12
Explained Variation as a %	98.8 %
Relative Model Error	1.21 %
Estimation Interval	1981Q2-2015Q1
Observations	136

The interpretations of the current elasticity estimates are as follows:

With respect to changes in fuel prices at the pump (which do include state, federal, and, in some cases, local fuel taxes), fuel consumption is very inelastic. That is, percentage changes in fuel use are far less than proportional to percentage changes in fuel cost. The current estimate indicates that a 10 percent increase in gas prices causes only 0.9 percent decrease in fuel use in the short run. This is consistent with economic behavior that exhibits a derived demand. Fuel is not desired by drivers for direct utility, but as an intermediate “input” toward utility creation in commuting and recreational/leisure activities.

Even in the short run where the capital is fixed, fuel price impacts are not necessarily immediate, but are distributed over a number of periods, which in the model’s case is a period is one quarter. The estimated models over time have revealed persistent price responses for a span of 4 to 5 quarters. However, the last 6-7 years have found the largest impact in the contemporaneous quarter (about an elasticity of 0.4 or roughly 43 percent of the entire short run sensitivity). Prior to that, the largest impact of a price change was usually about 2 quarters later.

Increases in the fuel efficiency of cars and light trucks/SUVs should reduce the demand for motor fuels, all else equal. Light vehicles are then able to accomplish the feat of covering the same vehicle miles of travel with somewhat fewer gallons. This effect is statistically significant in the econometric estimates, and of the expected inverse (or negative) relationship. However, the estimated elasticity with respect to fuel efficiency and consumption has always been quite minuscule. Currently, the empirical results indicate that a 10 percent increase in fuel efficiency begets only a 1.6 percent drop in motor fuels usage. Moreover, a ten percent improvement in the miles-per-gallon (MPG) of the light duty vehicle fleet does not occur rapidly. Presently the average is approximately 21.0 MPG. A ten percent improvement would amount to a gain of 2.1 miles per gallon. However, the fuel efficiency of the slowly aging vehicle fleet only changes quite gradually: at roughly a rate of about 1.6 percent annually. At this rate, for a 10 percent improvement to be realized, it would require roughly 5 to 6 years to transpire under present assumptions.

More dominant, by far, in affecting travel demand and the resulting use of motor fuels is the pace of economic activity in the state. This is represented in the estimated equation with a multitude of economic factors. First, Oregon’s total non-farm employment is a key explanatory variable for fuel usage; nevertheless, the sensitivity is not high. A 10 percent increase in employment generates about a 2.3 percent increase in fuel consumption as the increase in economic activity spurs an increase in travel demand by businesses and households. Secondly, the amount of purchasing power (adjusted for inflation) that drives consumer spending equally as significant in explaining fuel usage. A 10 percent increase in real personal income statewide spawns a 2.4 percent increase in gallons consumed. Finally, the condition of the overall labor market as a whole (as captured by the state’s labor force participation ratio (LFPR) helps to explain fuel demand. The ratio is comprised of the total civilian labor force (employed and unemployed) relative to Oregon’s working age population. Since the onset of the financial crisis in 2007-8, considerable note has been made pointing out the lowest ratios since the late 1970s. This pronounced structural shift in the overall labor market helps explain the lackluster fuel consumption coming out of the deep recession. If the ratio were reverse its current declining pattern, a 10 percent increase in the ration would generate a 1.2 percent increase in fuel usage as the labor markets becomes more vibrant.

The three aforementioned factors serve as a scale or size variable relating aggregate economy with the overall level of gallons used. A simultaneous increase of 10 percent in all three would produce a composite impact of nearly 6 percent in increased fuel use (simply the sum of the prior three elasticity estimates). This would suggest decreasing “returns” to scale in that the increase is well less than proportional, as has been the case in model estimation for the past 12 years.

Some of the statistics from the foregoing coefficient estimation are illustrative of the descriptive capability of the model. The percent of variation in fuel consumption (adjusted for degrees of freedom) explained by the combination of all variables is nearly 99 percent. The relative precision is 1.2 percent of average fuel usage.

§7. Considerations Having to Do with Assumptions Underlying the Highway Fund Forecasts

The left hand columns of Tables 4.1, 5.1, and 6.1 enumerate the bulk of the variables or assumptions that drive the revenue forecasts. The assumptions originate mostly from two primary sources, although there are some others that weave into the forecast specifications relating to DMV transactions.

The first set emanates from the *Oregon Economic Forecast* developed by DAS-Office of Economic Analysis. The variables here – such as Oregon Total Non-farm Employment and Oregon personal income – serve as very important and direct links of causation driving travel demands and driver/vehicle transactions to enable access to the state transportation network. The state economic forecasts are themselves closely connected to conditions in the national economy, and to a lesser extent to global factors (crude oil prices and foreign exchange rates as they affect Oregon’s exports abroad). The macro assumptions come from a very comprehensive macro-econometric forecast model developed by IHS-Global Insights (GII), a venerable economic forecast and industry analysis organization.

Since the breadth of the Oregon-specific is somewhat restricted, the State Highway Fund revenue model augments the assumption set with variables which are forecast in the national economic model by GII. For instance, industrial production indexes and industry-specific generated output variables are generally unavailable at the state level. In these instances, national production data are used as surrogates.

Another example pertains to the fuel efficiency of the light duty vehicle fleet of passenger cars and pickups/SUVs. Miles per gallon achieved by light vehicles are a significant factor in influencing fuel usage, along with driving habits and driver behavior. Nevertheless, it was shown above that the sensitivity of total taxable fuel consumption to MPG is comparatively minute, although still statistically significant. Currently, and consistently over prior practice, lack of a valid Oregon-specific variable for MPG necessitates using a nationwide measure as a surrogate. Notwithstanding, the Economics Unit has been engaged in an effort to construct an Oregon-specific measure for fuel efficiency of the light duty vehicle fleet.

An initiative was started in 2009 to develop a MPG measure for the state specifically. Using a snapshot of the light duty vehicle fleet from ODOT’s Driver and Motor Vehicle Division, for each vehicle in the master file at a point in time the VIN is matched to the federal EPA’s fuel efficiency values obtained from

manufacturers under varying, standardized laboratory conditions. A composite MPG estimate is derived by averaging across the population of all light vehicles in the master file. This is essentially a census approach, in contrast to random sampling.

Consistently, this approach appears to overstate what are probably more reasonable MPG numbers. The disparity is on the order of 5 to 8 percent. The estimates are probably overstated for several reasons owing to limitations in the EPA fuel efficiency numbers.

First, EPA estimates reported on the window stickers of new vehicles are well known to possess an upward bias or overstatement. Actual driving conditions and patterns use more fuel on average than the OEM-run laboratories indicate in the EPA numbers. So, the EPA MPG numbers and the CAFÉ standards are overly sanguine in real world driving conditions and habits.

Second, the market penetration of new vehicles trumps mandates governing how much fuel a car or light truck/SUV should use. Consumer choice in the market place is governed, however, by household economics and preferences. Fuel efficiency comes with higher capital cost and reduced operating costs, but the paybacks can be quite long—especially under lower fuel prices. Manufacturing quality seems to always improve; so the median age of the light duty fleet is always getting longer—approaching nearly 12 years presently. The stock of the entire fleet of light duty vehicles therefore changes very slowly, with new car standards having only a small effect overall. And the trend of an aging fleet continues, at an average rate of 1.5 percent per year. Moreover, while car and light truck/SUV buyers have mobility in mind at acceptable running costs, they also value highly the utility of the vehicle. With expanding recreational uses, utility may trump fuel economy in a significant number of purchasing decisions.

Elements such as the foregoing create a disparity between the EPA laboratory numbers and the results from real world behavior. Notwithstanding the upward bias problems, there is also a severe limitation in the historical breadth of the Oregon-specific MPG numbers. Given the structure of the vehicle master file, observations on the composition of the light vehicle fleet are not available prior to 2009. As a result, the estimation interval would have to be materially truncated for parameter estimation, or some form of an ad hoc, synthetic construction would have to be cobbled together. Both paths are unsatisfactory at this juncture.

While using an Oregon-specific measure for MPG over a nationwide measure may be compelling, the statistical aspect may not really be promising. The reason lies in the variance—a measure of dispersion around the mean—which is what matters in obtaining a least squares estimate of the sensitivity, along with covariances. Even if the average MPG in Oregon is different from the national one due to some difference in fleet makeup, it is unlikely that the variances differ materially to make any substantial difference in the sensitivity estimate. Very little is lost, therefore, in using the nationwide time series which have behavioral responses to real world conditions embedded in them, in contrast to EPA laboratory results of dubious accuracy.