Development of the Truck Registration Forecasting Model Used by Washington State

For The Transportation Revenue Forecast Council

Washington State Department of Transportation

Budget and Financial Analysis Division - Economic Analysis

Summary

From April through August, 2012, the Washington State Department of Transportation (WSDOT) and the Washington State Transportation Revenue Forecast Council (TRFC) conducted a study of the forecast model used to forecast truck registrations and revenue. This study examined the performance of the forecast methods used from the 1970s to the present; looked at alternative forecasting models and variables; and considered alternative methods for estimating revenues from the truck registration forecast. This process was completed under the supervision of a work group consisting of representatives from the various agencies making up the TRFC (appendix A). The work of examining the model was done by the WSDOT Economic Analysis License, Permits, and Fees (LPF) forecaster who presented his findings at four work group review meetings. At the review meetings, members of the work group would make recommendations for further analysis. The work group chose an annual econometric model that estimates annual truck registrations using Washington Retail Employment as the primary predictor variable. A log-log model is used where trucks are regressed on retail employment using ordinary least squares. A dummy variable is also used to account for a period of questionable data. This model was first used in the TRFC September 2012 forecast. After developing a new forecast methodology, we developed an improved methodology for calculating revenue from the new forecast. The new methodology simplified and streamlined a process that had been complicated through a series of legislative changes. The new methodology allows analysts to do scenario analysis on proposed fee changes.

Prior to 2012 Review

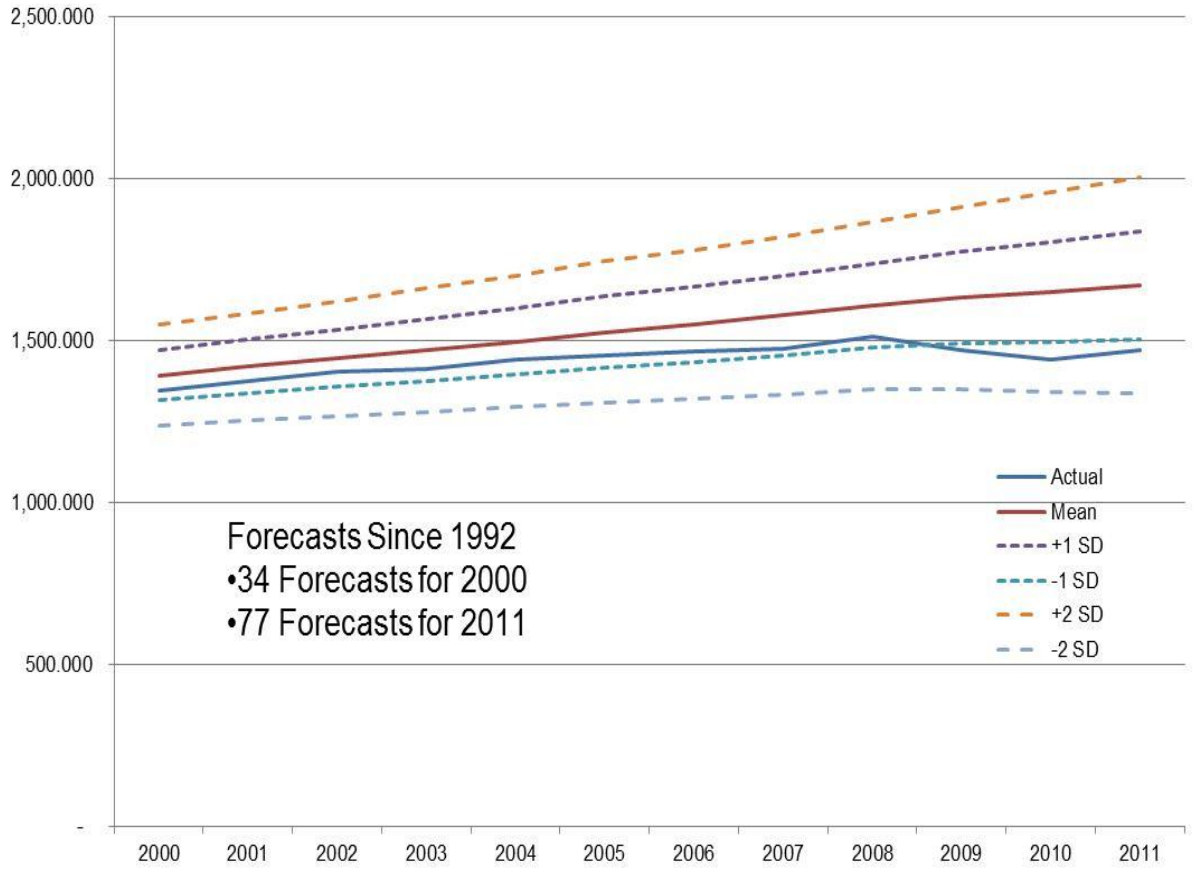
Prior to this review, the truck registration model used personal income as forecasted by the Washington State Economic Revenue Forecast Council (ERFC) for the near term forecast and population growth rates for the long term. This method had been used for the quarterly forecast since 2006. Prior to 2006, the truck registration forecast only used personal income; however, since the ERFC only forecasts the current biennium plus one full biennium out and the TRFC forecasts for a period of 16 years, WSDOT grew personal income at a rate of roughly 1% per year for the rest of the forecast period (Schmidt et. al., Transportation Revenue Forecasting Technical Workgroup, September 29, 2006). Because Washington State's Office of Financial Management (OFM) also extended personal income, but at a much higher rate, the 2006 Transportation Revenue Forecasting Technical Workgroup decided the use of two different

income forecasts could be confusing and decided to use OFM's population forecast for the extended period (See Appendix B).

Why Look for a New Model?

The truck registration forecast model used by WSDOT for the TRFC quarterly forecasts routinely over-forecasted truck registrations (Figure 1). Even though there was a tendency to over-forecast truck registrations, until 2008, actual registrations fell within one standard deviation of the mean forecast. After 2008, actual truck registrations fell within two standard deviations. Figure 1 shows the projected truck registrations for past forecasts for Fiscal Years 2000 through 2011 and the first and second standard deviations for those forecast. There

Figure 1. Actual Registrations Compared to Forecast.



were 34 forecasts for FY 2000, but because forecasting requirements changed, by 2011, there were 77 forecasts predicting registrations for that year. Since the TRFC currently conducts forecasts over a sixteen year horizon, a question one may ask is, "how good is the forecast in both the short and long term?" The answer to that question is the forecast is fairly accurate for truck registrations one to two years out, but rapidly loses accuracy three years and beyond.

Figure 2 compares truck forecasts between June 1992 through September 2012 for one, two, three, four, six and ten years in the future to actual registrations for a given year. For forecasts one year out, forecasted truck registrations are over actual registrations by an average of 1.59%. For two years in the future, forecasts are 2.81% over actual truck registrations.

Figure 2. Truck Registration Forecast Deviations, 2012

	Mean	Median	Min	Max
1 year	1.59%	1.29%	0.02%	6.50%
Obs	65.00			
2 years	2.81%	2.33%	0.01%	10.10%
Obs	62.00			
3 years	4.30%	2.96%	0.10%	12.88%
Obs	62.00			
4 years	5.87%	3.98%	0.22%	15.15%
Obs	56.00			
6 years	6.29%	4.74%	0.05%	18.53%
Obs	50.00			
10 years	9.53%	8.91%	1.82%	20.34%
Obs	38.00			

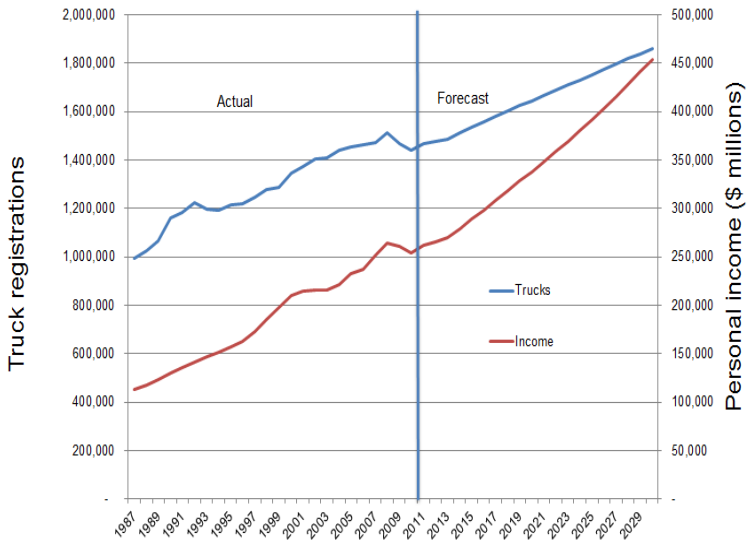
Figure 3. Truck Registration Forecast Deviations. 2006

	Mean	Median	Min	Max
1 year	1.93%	1.44%	0.01%	9.60%
Obs	44.00			
2 years	3.21%	2.52%	0.10%	11.02%
Obs	41.00			
3 years	4.35%	2.94%	0.22%	13.49%
Obs	38.00			
4 years	5.04%	3.98%	0.05%	15.15%
Obs	35.00			
6 years	7.13%	5.59%	0.08%	18.98%
Obs	29.00			
10 years	13.85%	12.57%	8.66%	21.11%
Obs	17.00			

Forecasting for ten years in the future, truck forecasts average 9.53% higher than actual registrations for a forecasted year. While near term forecasts are reasonably accurate this shows that, in the long term, forecasts are very high.

This issue was identified in the previous forecast review conducted in 2006 (Figure 3). At that time, the forecast workgroup chose to use the population forecast to bring down the long-term forecast, since population is only forecasted to grow at about 1% per year. In 2006, forecasts for ten years out were over the actual by an average of 13.85%. While using population has improved the long term forecast, (9.53% in Figure 2, above) there is room for improvement.

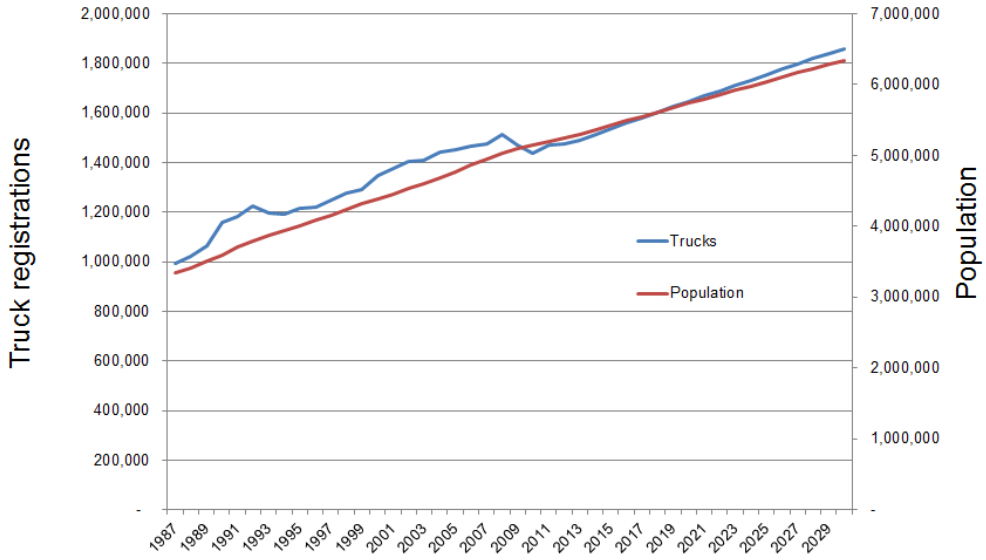
Figure 4. Truck Registrations and Personal Income



Another issue with the truck registration forecast is that changes in truck registrations from year to year tend to be more volatile than either personal income or population. While truck registrations, personal income, and population are highly correlated, truck registrations appear to react to short-term business cycles while personal income and population do

not. Truck registration growth rates appear to have plateaued since 2001, while personal income and population continue to grow at higher rates (Figures 4 & 5).

Figure 5. Truck Registrations and Population



Breakdown of Truck Registrations and Revenue

Before delving into the selection of forecast variables, knowledge of what, exactly, is being forecasted is helpful. When discussing truck forecasting, most people, even those professionally involved in the issue, think of trucks as commercial tractors and semitrailers. While these are significant in the Washington's fleet of 1.4 million trucks, almost 85% of the trucks forecasted are pickup trucks. There are several other complicating categories. About 0.14% of the trucks are registered as "fixed load" vehicles. These are primarily utility type trucks that are not used for cargo. Some of the trucks in this category include bucket trucks or trucks that carry drill rigs. Another group of trucks are farm trucks. This group makes up just over 1% of Washington's fleet. Log trucks make up about 0.04% of the fleet. The category of vehicle most people think of when we discuss this category of vehicle, commercial trucks, makes up just over 14% of the state's fleet. This category also includes local delivery vans, not just tractor-semitrailer rigs. To complicate matters further, vehicles that would normally register as passenger cars, could be registered as a truck in order to get a commercial license plate. Finally, all of the trucks discussed above are registered based on fuel type, which includes gas, diesel, or other fuels.

Further complicating truck registrations, in Washington, under RCW 46.17.355 trucks pay registration fees based on weight at 2,000 pound intervals from 4,000 lbs. and below to

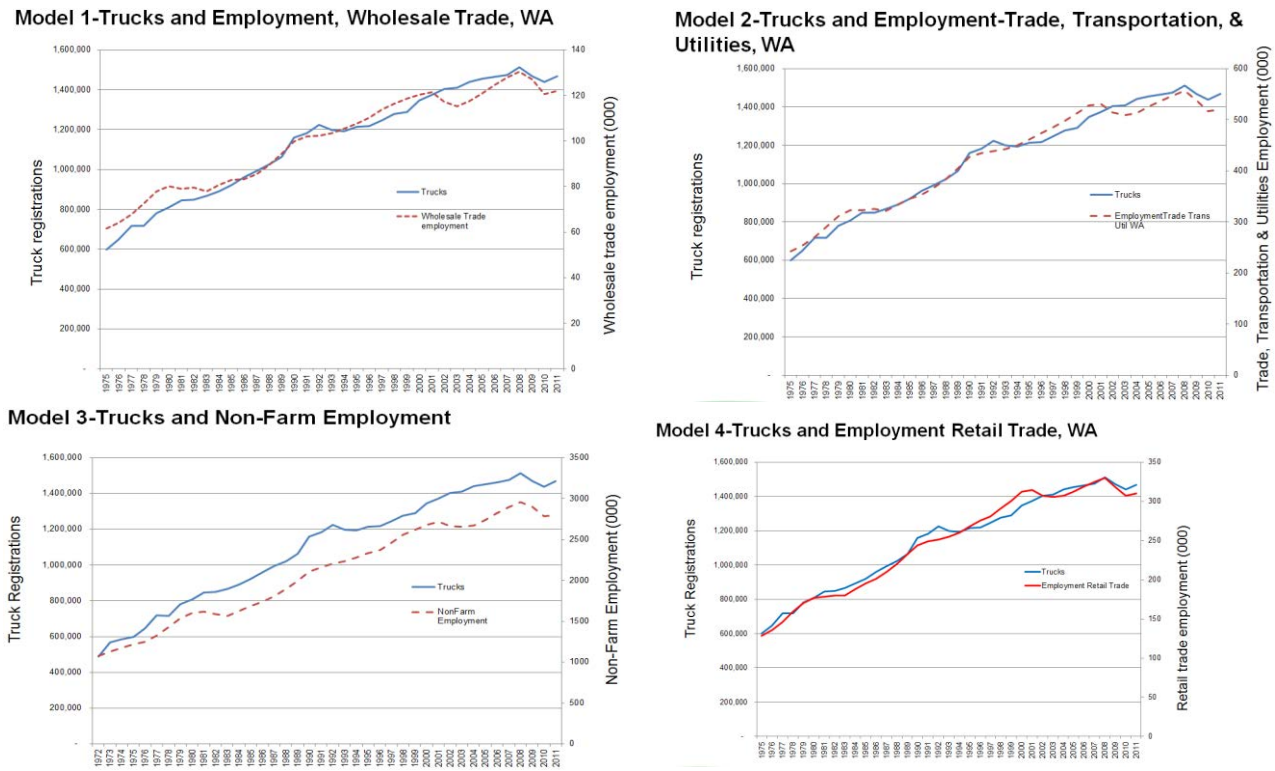
105,500 lbs. The fee is also modified based on whether the truck is intended to haul logs, trailers, or are used as a farm truck (RCW 46.17.330). Thus, there are over 200 weight categories a truck could register in. It is often assumed that registration of trucks is by actual weight. This is not the case. Truck registration is based on declared gross weight. This means the truck owner registers the truck for the total weight the owner plans to haul in the truck. For most pickup trucks, this is assumed to be 150% of the truck's scale weight, however for commercial trucks, it depends on how much the owner believes the truck will carry for the next year. Two different owners could register identical trucks at 40,000 lbs. and 80,000 lbs. depending on what each owner thought they would carry or how their trucks are used. Also, depending on changes in business cycle, a truck owner may register a truck at 40,000 lbs. one year and register the same truck at 80,000 lbs. the next year.

It is tempting to attempt to forecast vehicles by use type or weight. We have explored various methods to do that in the past and have found that doing so creates very complex forecast models that are neither accurate nor statistically significant. The most satisfactory method of forecasting trucks is to forecast the entire fleet, then to estimate various categories as necessary, largely because of the issues discussed above. When the fleet is subdivided, no variable has a predictive variable (correlation) higher than 80% and many are below 50%. By forecasting the entire fleet, we find more independent variables from which to choose and accuracy of the forecasts greatly improves.

Forecast Variables Considered

Washington State's Economic Revenue Forecast Council forecasts hundreds of demographic and economic variables that could be used in various forecasts. For the first meeting of the truck forecast work group, the LPF forecaster examined 35 independent economic and demographic variables which may be relevant to truck registrations (Appendix C). The first step was to see how closely these variables correlated to truck registrations. The forecaster chose the variables with a correlation greater than the correlation of trucks to personal income (R^2=0.95) and trucks to Washington population over 18(R^2=0.98) for further review. This resulted in four variables for further consideration: Washington Wholesale Trade Employment (R^2=0.9871); Washington Trade, Transportation, and Utilities Employment (R^2=0.9902); Washington Nonfarm Payroll Employment (R^2=0.9917); and Washington Retail Trade Employment (R^2=0.992). Next, we developed regression models 1 through 4 based using each variable. We plotted each variable against historical truck registrations (Figure 6).

Figure 6. Forecast Models 1-4



Using the Economic Time Series Forecasting module in SAS, we developed log-log models on each variable. All of the models yielded acceptable parametric statistics, however, of the four variables, Model 4 using Washington Retail Trade Employment yielded the best parametric statistics for the independent variable (Figure 7). Model 4 also yielded the best statistics of fit across the board (Figure 8), although the differences in many cases were quite small.

Figure 7. Models 1-4 Comparison: Parametric Statistics

Model Comparison: Parametric Statistics

	Model 1-Wholesale Trade, WA (logged)				Model 2-Transportation, Trade, Utilities, WA (logged)			
Parameter	Estimate	Std. Error	T Score	Prob	Estimate	Std. Error	T Score	Prob
Intercept	9.7753	0.6822	14.3269	<.0001	7.45762	0.2623	28.4335	<.0001
Autoregressive lag	0.97414	0.0427	22.808	<.0001	0.69037	0.1269	5.4414	<.0001
Variable	0.89462	0.1418	6.3085	<.0001	1.07085	0.04326	24.584	<.0001
Variance	0.0007721				0.000591			

	Model 3-Nonfarm Employment, WA (logged)				Model 4-Retail Trade, WA (logged)			
Parameter	Estimate	Std. Error	T Score	Prob	Estimate	Std. Error	T Score	Prob
Intercept	5.84312	0.4313	13.5475	<.0001	8.7127	0.1773	49.1478	<.0001
Autoregressive lag	0.78144	0.1009	7.7412	<.0001	0.64296	0.1338	4.8057	<.0001
Variable	1.05314	0.0568	18.5333	<.0001	0.95016	0.0324	29.3017	<.0001
Variance	0.00092				0.0005194			

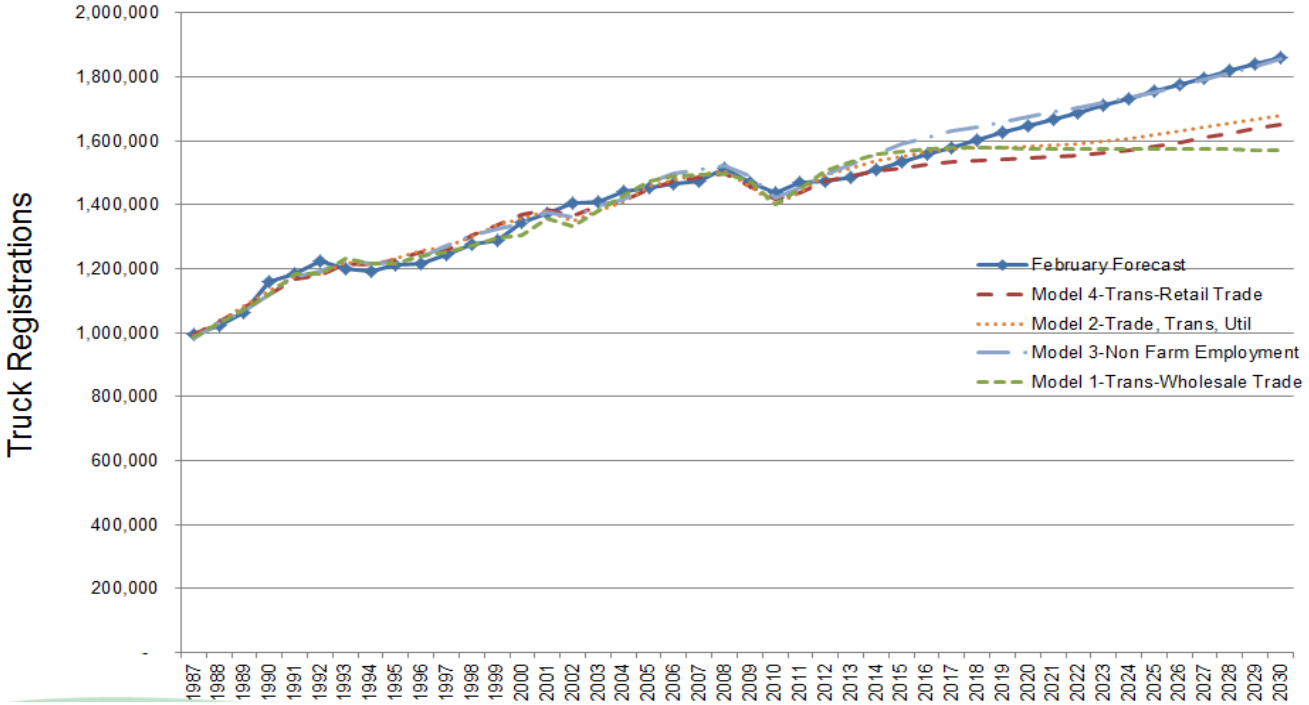
Figure 8. Models 1-4 Statistics of Fit

Statistics of Fit

	Model 1-Wholesale Trade (logged)	Model 2-Trans, Trade, Utilities (logged)	Model 3-Nonfarm Employment (logged)	Model 4-Retail Trade (logged)
Total Sum of Squares (Uncorrected)	5.07E+13	5.07E+13	5.16E+13	**5.07E+13**
Total Sum of Squares (Corrected)	2.73E+12	2.73E+12	3.71E+12	**2.73E+12**
Sum of Square Error	3.83E+10	2.28E+10	2.70E+10	**1.96E+10**
Mean Square Error	1,034,347,094	616,390,645	675,437,974	**529,443,716**
Root Mean Square Error	32,161.3	24,827.0	25,989.2	**23,009.6**
Mean Absolute Percent Error	2.44343	1.88668	2.33274	**1.72779**
Mean Absolute Error	24,066.9	20,462.4	21,921.4	**18,808.3**
R-Square	0.98600	0.99200	0.99300	**0.99300**
Adjusted R-Square	0.98500	0.99100	0.99200	**0.99200**
Mean Error	5,344.10000	874.72656	587.26263	**528.41560**
Mean Percent Error	0.28794	0.00275	0.09938	**-0.01061**

Figure 9 shows a comparison of how each model backcasts history and forecasts the future. Each model was plotted against history and the February 2012 forecast using the previous truck model. In regards to the backcast, all of the models provide similar results. Given the statistics of fit, this is expected. The forecasts are a different story. All of the models forecasted slightly lower truck registrations in the first two years of the forecast. After that, the models diverge. Model 1, Wholesale Trade Employment for Washington, exceeded the February forecast by the forecast period, then dropped below the February forecast by year 2020. This model is unique in

Figure 9. Current Forecast and Top 4 Model Comparisons



that after 2020, the model predicts a decline in truck registrations throughout the forecast horizon.

Model 2, using Trade, Transportation, and Utilities Employment for Washington as the independent variable provides very similar results to Model 1, however, Model 2 shows an increase in truck registrations, year over year, when Model 1 begins showing a year over year decline in registrations. Model 3, based on Non-Farm Employment is unique among the various variables. While it behaves in a similar manner as the previous variables through the year 2015, the model continues to grow truck registrations at a high rate, and, by the year 2023, it begins to mirror the February forecast model. Finally, Model 4, using Retail Trade Employment, creates a forecast curve very similar in shape to Model 2 (Trade, Transportation, and Utilities), although the predicted truck registrations are somewhat smaller.

Unit Root and White Noise Tests. To assist in choosing a forecast model, the workgroup also looked at the white noise and unit root tests. While Model 1 was the least affected by white noise, it had very poor unit root test statistics. All of the other tests showed acceptable white noise tests and all of the other tests showed unit root issues. After reviewing the models at this point, WSDOT-Economic Analysis recommended using a model based on Washington Employment in Transportation Retail Trade because it had the highest descriptive statistics and statistics of fit. It produced a truck registration backcast closest to historical truck registration numbers, and most similar to both fuel and vehicle miles travelled forecasts. A drawback to this model was the unit root tests showed the model is nonstationary. The work group asked to see additional testing.

For the next round of model testing, the workgroup asked to see other methods of forecasting truck registrations based on various truck owner demographics, regional registrations, as a portion of national truck registrations, and incorporating the impact of federal fuel standards for trucks. During this round, we explored using a dummy variable to explain a spike in registrations from 1990 to 1992 that does not seem to relate to any of the possible explanatory variables. We also looked at variations in the Retail Trade employment model to correct the unit root issue.

Regional Demographics. To develop models based on truck owner demographics, we first had to find information that described truck owners. We found a report by the Specialty Equipment Market Association called the *2005 Light-Truck Personalization Report*. From that report we learned that, nationally, most truck owners are between the ages of 35 to 64, with a mean age of 46.67 years. Further, that report tells us that 89.6% of the nation's light trucks are owned by men, while the remainder is owned by women. Based on this information, we looked at six population sub-groups for Washington: Males aged 35-64, Females aged 35-64, Total Population aged 35-64, Males aged 18 and over, Females aged 18 and over, and Total Population aged 18 and over. We looked at the various 18 over categories because the total population, 18 and over, is used in the current forecast methodology. The results of this exercise were surprising. Of the six

variables, the highest correlation was for the Washington population of women, 18 and over. This variable also had the highest parametric statistics and statistics of fit. Forecast models developed with the population variables all yielded similar results as the February 2012 forecast using population. We rejected all of these variables because:

- Other variables provide higher statistics of fit
- Population variables are only adjusted once each year
- Population variables are not sensitive to short-term economic conditions

The best variable of this group, Female population, 18 and over, was also counterintuitive. While statistically, it "best explains" truck registrations, it is difficult to understand how that should be the case, given what we know about ownership trends.

The workgroup also asked to test Washington regional demographics. Here, the assumption was that population changes in rural, unincorporated, and eastern Washington may have an important impact on truck registrations. Again, this was not the case. Western Washington had the highest correlations of the regional demographics. It is also interesting to note that while rural population had a higher correlation to truck registrations than urban registrations, population in incorporated areas were higher than unincorporated areas. No further testing was completed. These population sets suffer from the same problems cited above.

National Truck Registrations. The next group of models tested used National Truck Registrations and Federal CAFE Standards as variables. Two models incorporated National Truck Registrations. One predicted Washington truck registrations using National Trucks as the independent variable, the other used Washington Retail Employment and National Truck Registrations. While the model using National Truck Registration was significant, it was no better than other models tested. There is also difficulty in acquiring National Truck Registration forecasts. Most are updated once a year and they vary widely. The model using Retail Employment and National Truck Registrations did not perform as well as Retail Employment alone. Not only was the National Truck Registration variable not significant, the presence of that variable in the model degraded the significance of Retail Employment.

Dummy Variable and First Differencing. After running these models, we modified the Retail Employment Model, Model 4, by adding a dummy variable. The dummy variable was significant and improved the performance of the model, however, the presence of the dummy did not help the unit root issue. This lead to one more round of testing using first differences of the first four models. This had two objectives: to ensure retail trade employment was, indeed, the best variable; and to possibly correct for the stationarity issue in the variables.

When we first differenced the independent variables, we found that retail trade still had the best parametric statistics and statistics of fit; however, first differencing both the independent and dependent variables, led to different results. First differencing had little impact on the stationarity issue. Figure 10 compares the Statistics of Fit for the retail trade employment models.

After these tests, the work group settled on Model 4A, which uses Employment in Retail Trade Transportation as the independent variable, a dummy variable, AR1, and no 1st difference. All components of this model are significant, the model has good statistics of fit (generally the best of all models), and does not create overly aggressive forecasts.

Figure 10. Statistics of Fit Retail Employment Models

	Model 4- Retail Employment (logged)	Model 4A- Retail Employment and Dummy (logged	Model 4B- Retail Employment and Dummy (logged) Trucks 1st Difference
Total Sum of Squares (Uncorrected)	5.07E+13	5.07E+13	**4.943E+13**
Total Sum of Squares (Corrected)	2.73E+12	2.73E+12	**1.95E+12**
Sum of Square Error	1.96E+10	1.724+E10	**1.171E+10**
Mean Square Error	529,443,716	464,065,677	**344,497,354**
Root Mean Square Error	23,009.6	21,542.2	**18,560.6**
Mean Absolute Percent Error	1.72779	1.57565	**1.28134**
Mean Absolute Error	18,808.3	17,127.0	**14,471.2**
R-Square	0.99300	0.994	**0.994**
Adjusted R-Square	0.99200	0.983	**0.993**
Mean Error	**528.41560**	534.23184	-2573.3
Mean Percent Error	-0.01061	**-0.0098147**	-0.21249

Forecasting Revenue

Once a forecast of truck registrations is developed, the next step is to determine the revenue derived from registrations. This, technically, is not a forecast, but the calculation of revenue from the truck revenue forecasts. As previously discussed in this paper, trucks pay registration fees based on declared gross weight and can pay a fee ranging from $24.50 for a farm truck with a declared Gross Weight of 4,000 lbs. to $3,400 for a truck with a declared Gross Weight of 105,000 lbs. based on the schedules in RCWs 46.17.330 and 335. It is also possible for trucks to pay even less than the amounts in the schedules. Vehicle owners can and do register their vehicles for just part of a year. With many agricultural and commercial operations, trucks may only be required for part of the year, and truck owners will pay a prorated share of the annual fee.

To determine revenue, past practice had been to divide actual truck revenue collected and divide by the total number of trucks, giving a realized rate. Forecasted truck numbers were then multiplied by that rate to determine forecasted revenue. Due to several fee changes brought by initiatives or legislative action, the simple method of forecasting revenue required several adjustments that sought to isolate the impact of each of these changes. This allowed analysts to compare the impact a citizens' initiative and two legislative changes, one that reversed the impact of that initiative and one that increased fees on commercial vehicles, had on revenue.

In the course of the forecast examination, the work group determined that given the age of the last legislative change to vehicle registrations, it was no longer required to compare these older legislative changes and that the revenue calculation process should be simplified. However,

members of the House and Senate Transportation Committee staffs wanted a process that allowed them to use forecasted vehicle information to perform scenario analyses of proposed fee changes to schedules in RCWs 46.17.330 and 335. Using data generated from the Department of Licensing's accounting section on revenue collected for a monthly weight fee, we developed a method of estimating the total number of vehicles in each weight category. This allows us to estimate the amount of revenue generated by weight for any given quarterly forecast and allows analysts to do scenario analysis on proposed fee changes.

Appendix A

Transportation Revenue Forecast Council Truck Forecast Work Group

The Transportation Revenue Forecast Council consists of economists and technical staff from various Washington State agencies and legislative committees. The following personnel participated and contributed to the Truck Forecast Work Group:

Doug Vaughn, Director WSDOT Budget and Financial Analysis

Lizbeth Martin-Mahar, Ph. D., Assistant Director, WSDOT Budget and Financial Analysis, Economics Branch

Thomas L. R. Smith, Ph. D., Transportation Economist, Licenses, Permits, and Fees, WSDOT, Project Lead

Fanny N. Roberts, Ph. D., Transportation Economist, Fuel Usage and Revenue, WSDOT

Brian Calkins, Senior Researcher, WSDOT State Rail and Marine Division

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Lorrie Brown, Ph. D., Office of Financial Management, Forecasting

Eric Hansen, Office of Financial Management

Jim Albert, Office of Financial Management

Lance Carey, Economic and Revenue Forecast Council

Jerry Long, House Transportation Committee

Amanda Cecil, Senate Transportation Committee

Jean Du, Ph. D., Manager, Department of Licensing Economic Analysis

Alice Vogel, Department of Licensing Economic Analysis

Bob Plue, Department of Licensing Economic Analysis

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Appendix B

Excerpt from Transportation Revenue Forecasting Technical Workgroup Draft Report, September 29, 2006

Forecast Title: **Licenses, Permits, and Fees Truck Forecast**

Forecasting Methodology/Model:

- Methodology – The Washington State Passenger Truck Registration Forecast is derived from an econometric model that estimates annual registrations using adjusted Washington State Real Personal Income as the predictor variable. A log-log model is used where trucks are regressed on personal income using ordinary least squares.

- Equation – The linear form of the model is $\ln(\text{Trucks}) = \alpha + \beta\ln(\text{YP}) + \varepsilon$

  Where
  Trucks = Annual Registrations for trucks
  YP = Washington State Real Personal Income
  And
  ε = Stochastic disturbance on personal income.

  The model has an Adjusted R-squared of .991835, a Durbin-Watson statistic of 2.077055, and an F-statistic of 1944.554. The t-statistic for personal income is 5.577221.

- Forecast drivers – Truck registrations have a very strong positive correlation to real personal income. Over the last 30 years this relationship has held, however, most recently, the equation tends to slightly overestimate registrations. The model also tends to overlook situations like large increases to personal income through one-time distributions of dividends from companies like Microsoft. The close relationship of personal income to truck registrations could cause an unwary forecaster to predict large increases in registrations that would not materialize.

- Revisions – While there were no concerns raised by the Technical Workgroup about the forecast methodology, the Workgroup did raise a concern about the long term forecast of Real Personal Income. The Personal Income series used in the forecast is provided by the Washington State Economic and Revenue Forecast Council (ERFC). Their forecast of personal income only covers one full biennium. WSDOT extended that forecast by growing real per capita personal income at roughly 1 % per year. Concern was expressed that the Office of Financial Management (OFM) also creates an extended forecast and that it was markedly different from WSDOT's forecast.

  We tested the possibility of using OFM's extended forecast, however that forecast created growth rates for trucks that, in the judgment of the forecasters, could not be sustained. As a result, we decided to use population (18 years and older) as the independent variable for forecasting vehicles beyond the period covered by the ERFC forecast. The forecast uses ERFC's forecast of personal income to forecast the short-term

registration of vehicles and OFM's forecast of population (18 years and older) for the long term forecast.

Throughout the evaluation, we looked at a number of alternate predictor variables. While most had high correlations with vehicle registrations, personal income and population tend to have the strongest relationships. Additionally, the forecasting methods of other states were examined. Forecasting methods throughout the country range from increasing previous years actual registrations by a predetermined growth rate, to multiple variable forecast models. Most models tended to use personal income in some fashion, however.

Data:

- Data issues – Personal income and population data sets are readily available for use in forecasting. Vehicle registrations are provided monthly by the Department of Licensing (DOL), through their website at https://fortress.wa.gov./vsFeeDistribution/Default.asp?bhcp=1 . The Department of Transportation reviews these data regularly and works closely with DOL to clarify discrepancies.

Forecast assumptions:

- Critical assumptions – Prior to the Workgroup, the critical forecast assumption was that truck equations would be re-estimated to account for revisions to the history of state personal income, through the period provided in the ERFC forecast. For the period beyond ERFC's forecast, real per capita personal income was assumed to grow at the rate of 1% per year. As a result of Workgroup discussions on personal income, this assumption was changed. While ERFC's forecast of personal income is used, the forecast of vehicles beyond ERFC's forecast is based on the growth of population (18 and over) provided by OFM.

Forecast performance:

- Past performance – Forecast performance for trucks has been consistently good. For the period 1990 to 2005, the forecast one year out tends to over forecast passenger trucks by less than 1 %. Two years out, the forecast tends to over forecasts by 2.16 %. The forecast is also consistent from forecast to forecast, with an average variance of less than 1% between forecasts. Most variations beyond that are due to legislative changes.

Appendix C

Independent Variables Considered for the 2012 Truck Registration Modeling with Their Correlation Coefficients.

Variable	R^2	R^2 Adjusted
Washington Population Growth Relative to the U. S.	-0.1846	0.0341
Washington Employment Growth Relative to the U. S.	-0.2772	0.0741
Washington Personal Income	0.9537	0.9097
Washington Population over 18	0.9831	0.9664
Employment-Mining, WA	0.2186	0.0478
Employment-Printing & Related Support, WA	0.3575	0.1518
Employment-Transportation Equipment, WA	0.3897	0.1518
Employment-Aerospace, WA	0.4349	0.1891
Employment-Transportation Equipment, Excluding Aerospace, WA	-0.4988	0.2488
Employment-Paper & Paper Products, WA	-0.5167	0.2669
Employment-Manufacturing, WA	0.5297	0.2806
Employment-Computer & Electrical Products, WA	0.5625	0.3164
Employment-Nondurable Goods, WA	0.5785	0.3347
Employment-Other Nondurable Goods, WA	0.5925	0.351
Employment-Construction, Nonresidential, WA	0.8147	0.6638
Employment-Goods Producing, WA	0.8513	0.7247
Employment-Wood Products, WA	-0.8607	0.7409
Employment-Primary Metals, WA	-0.8707	0.7582
Employment-Fabricated Metal Products, WA	0.8991	0.8084
Employment-Other Durable Goods, WA	0.9073	0.8233
Employment-Machinery, WA	0.9077	0.824
Employment-Nonmetallic Mineral Products, WA	0.9257	0.857
Employment-Construction, WA	0.9264	0.8582
Employment-Electrical Equipment & Appliances, WA	0.9313	0.8673
Employment-Petroleum, Coal, Plastics, & Rubber Products, WA	0.9339	0.8721
Employment-Logging, WA	-0.9461	0.8952
Employment-Transportation & Warehousing	0.9581	0.918
Employment-Transportation, Warehousing, and Utilities, WA	0.9688	0.9386
Employment-Trade, Transportation, and Utilities	0.984	0.9682
Employment-Wholesale Trade, WA	**0.9871**	**0.9744**
Employment-Trade, Transportation, and Utilities, WA	**0.9902**	**0.9805**
Nonfarm Payroll Employment, WA	**0.9917**	**0.9834**
Employment-Retail Trade, WA	**0.992**	**0.984**

Note: R2 and R2 Adjusted were computed in an Excel Spreadsheet. These statistics may vary from those computed in SAS.