

Statewide Fuel Consumption Forecast Models

**Washington State Department of
Transportation – Economic Analysis**

Work Group Participants: Washington State Department of Transportation, Washington State Office of Financial Management, Washington Department of Licensing, Washington State Economic and Revenue Forecast Council, and House and Senate Legislative staff

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Acknowledgements

In April 2010, the Washington State Department of Transportation formed a Technical Workgroup to develop revised statewide fuel consumption forecast models. The Technical Workgroup met numerous times between April and October 2010 to review the current gasoline and diesel forecasts and analyze methods for modifying the forecast models. Presentations and group discussions examined data issues, seasonality, forecast methodologies, critical assumptions, forecast drivers and forecast performance. The following persons participated in the Technical Workgroup:

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Most of the analysis of the forecasts that appears in this study is the result of the seven months of research that this group devoted to evaluating the fuel consumption forecast models. Special thanks go to them for devoting their time to studying and improving the forecasting process for fuel consumption in Washington state.

Executive Summary

FUEL CONSUMPTION DATA AND PAST FORECAST METHODOLOGY

- For more than 40 years WSDOT-Economic Analysis has been forecasting Washington fuel consumption statewide
 - Past Methodology: The old quarterly gas consumption forecast model consisted of the US oil price index for petroleum products adjusted for inflation, US fuel efficiency and a dummy variable for periods of severe oil supply shortages as independent variables in the regression model. The old linear quarterly diesel consumption forecast model consisted of a 4-quarter moving average of Washington personal income.
 - Accuracy of Past Forecast Models: The past gasoline forecast model has been consistently overestimating actual gas consumption for years. In recent years, the model forecasts have declined in accuracy predicting actuals. Gas consumption in 2010 came in more than two standard deviations from the mean forecast. In prior years, the diesel forecast model predictions underestimated actual consumption. In 2009 and 2010, the forecast model overestimated actual diesel consumption.
- Prior reviews of our Washington transportation revenues highlighted the potential risks to our current fuel tax forecasts¹

FACTORS AFFECTING FUEL CONSUMPTION

- There are many factors which determine the number of vehicles on the roadways, number of trips taken per driver, distance traveled and fuel consumed.
- Numerous independent variables were tested in a econometric forecast model for fuel consumption
 - Gas prices – as well as percentage change in prices
 - Washington motor vehicle registrations: gas and diesel powered vehicles
 - Washington employment: non-agricultural and various industry specific employment
 - Washington personal income
 - Washington personal income per capita
 - Washington wages and salaries
 - Total and driver aged population
 - Fuel efficiency
 - University of Michigan consumer sentiment
 - US industrial production
 - US consumption of fuel
 - US corporate profits
 - Washington taxable business income
- Various model functional forms and the necessity for lagging independent variables were also considered in revised gas and diesel consumption forecast models

¹ JTC 2010 Long-term Transportation Funding study

- Truncated models as well as quarterly and annual models were also considered during the work group review process.

NEW STATEWIDE FUEL CONSUMPTION FORECAST METHODOLOGY

- The final statewide econometric gasoline and diesel consumption forecast models were determined after considering various forecast model specifications. Quarterly and annual fuel consumption models will be used in the new forecasting methodology.
- Both final quarterly and annual gas and diesel consumption models are of log-log functional form.
 - Gasoline consumption quarterly model includes the log of the following independent variables:
 - Washington non-agricultural employment
 - Composite variable of Washington gas prices and fuel efficiency
 - Dummy variable for periods of severe oil supply shortages
 - Gasoline consumption annual model includes the log of the following independent variables:
 - Washington non- agricultural employment (first difference)
 - Washington population (first difference)
 - Composite variable of Washington gas prices and fuel efficiency
 - Diesel consumption quarterly model includes the log of the following independent variables:
 - Washington employment – trade, transportation and utilities sectors
 - Washington real personal income
 - Diesel consumption annual model includes the log of the following independent variables:
 - Washington employment – trade, transportation and utilities sectors
 - Washington real personal income
- Each independent variable has its own separate and distinct forecast which can be used to project fuel consumption
- These regression models were selected because they had the best overall fit, significant t-statistics and other critical statistics. In addition, the economic variables in the models had a close nexus to fuel consumption.
- These new forecast models will assist us in separating the near-term and long-term impacts on fuel consumption.

IMPACTS

- The impacts of implementing the new fuel consumption forecast models using September 2010 economic variables were analyzed. The new gas consumption forecast model will have minimal impact in the near-term but significant impacts in the long-run. The diesel consumption forecast model will generally result in slightly higher diesel consumption forecasts. The following results were found:
 - 10-year impacts:
 - New gas consumption model will lower gas tax revenue by a total of \$518 million from September 2010 forecast

Executive Summary

- New diesel consumption model will increase diesel tax revenue by a total of \$105 million from September 2010 forecast
- Combined effect is a reduction in fuel tax revenue of \$413 million from current forecast
- 16-year impacts:
 - New gas consumption model will lower gas tax revenue by a total of \$1.68 billion from September 2010 forecast
 - New diesel consumption model will increase diesel tax revenue by a total of \$89 million from September 2010 forecast
 - Combined effect is a reduction in fuel tax revenue of \$1.6 billion from current forecast

Chapter 1: Background- Fuel Consumption Models

Washington State Department of Transportation has been producing a statewide forecast of fuel consumption for more than 40 years. Periodically over the years of forecasting transportation revenues, WSDOT and OFM have organized work groups of forecasters to review and examine the transportation forecast models for various revenue sources. Even as recently as 2006, OFM reviewed the methodology for all the major transportation forecast models. The 2006 work group did not advise any modifications to the gas and diesel consumption models but they did express concern over not having personal income or other variable measuring economic activity in the gas consumption model. The work group acknowledged the uncertainty of having a gas model which was so dependent on gas prices which are difficult to forecast. There was also concern expressed over the short-term nature of the models.

This forecast is split out for both gasoline and diesel consumption which has been a product of econometric fuel consumption forecast models that were performed each quarter. In recent years with our severe economic recession, the forecast models have not performed well. This is not too surprising. After examining the gasoline and diesel model performance over a longer period of time prior to the recent recession, the results reveal that both fuel consumption models have consistently not been performing well for several years but in opposite directions. The gasoline consumption forecast model has consistently overestimated fuel consumption and the diesel consumption forecast model has underestimated diesel consumption.

Some of the reasons for the formation of this 2010 work group to review the Department's fuel consumption forecast models were due to the following:

- To examine past performance of the fuel consumption forecast models which showed trends of inaccurate forecasts consistently overestimating gas and underestimating diesel consumption
- To reflect more recent trends of flattened national and Washington state gas consumption since the accuracy of the past steep upward trending forecasts had been questioned
- To study the reliance on one dominant economic variable, gas prices, which are known to be very volatile
- To address changing fuel efficiency standards on fuel consumption in forecast models
- To consider other models besides a quarterly forecast model for the long-term forecasts
- To survey other states to see which economic variables they are using in their fuel consumption forecast models

Trends in Washington's Gasoline Consumption

Figure 1 shows Washington's historical quarterly seasonally adjusted and unadjusted gasoline consumption since 1978. As the graph reveals, quarterly gasoline consumption has a seasonal pattern. The typical fuel consumption pattern is the first quarter consumption is the lowest of the year with consumption rising until the third quarter. The third quarter is usually the highest quarter. Fuel consumption then declines again in the last quarter, but not as low as in the first quarter of the year. Gasoline consumption quarterly trends are a function of the driving activities of Washington residents and visitors who tend to drive more in the summer and during holiday periods like Memorial Day, 4th of July and Labor Day weekends. Since 1978, Washington annualized gasoline consumption has increased from 1.85 billion gallons of gasoline consumed in the first quarter of 1978 to 2.54 billion gallons of gasoline in the last quarter for 2009. During the early 1980s when we had a smaller, less severe recession, there was also a dip in gasoline consumption; Washington state consumption recovered slowly. Between 1987 and

1999, fuel consumption rose in the state. Since 2000, gas consumption has flattened and the average annual growth rate for gas consumption has even declined slightly over the past 10 years.

FIGURE 1. QUARTERLY NON-SEASONALLY ADJUSTED AND SEASONALLY ADJUSTED ANNUALIZED GASOLINE CONSUMPTION IN WASHINGTON SINCE 1978 (MILLIONS OF GALLONS)

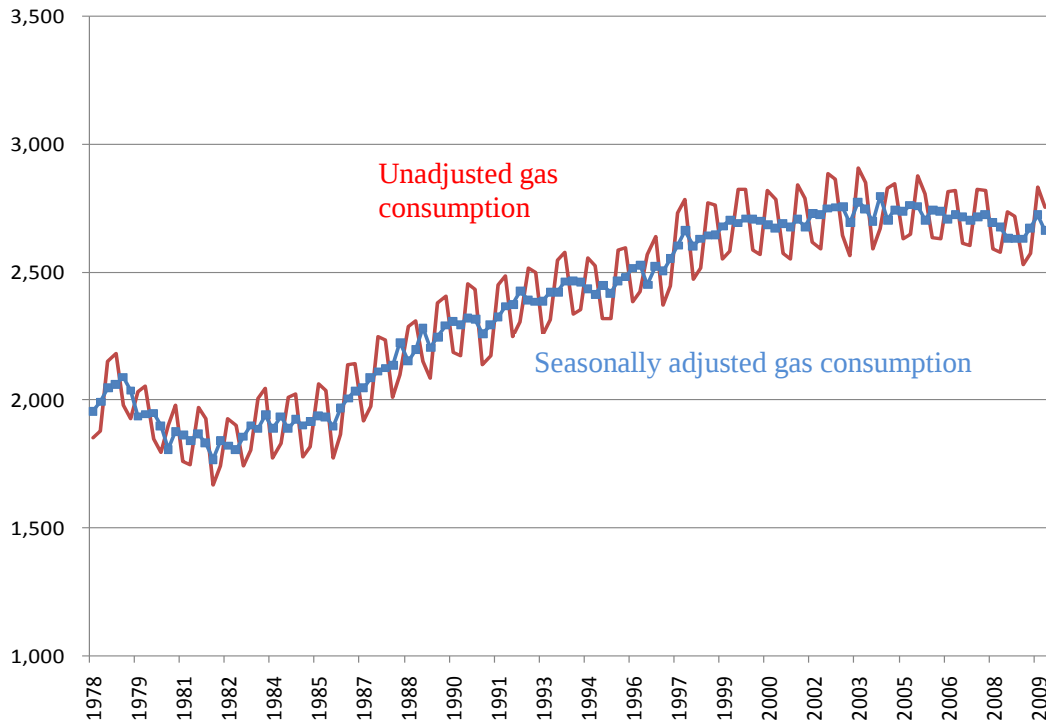
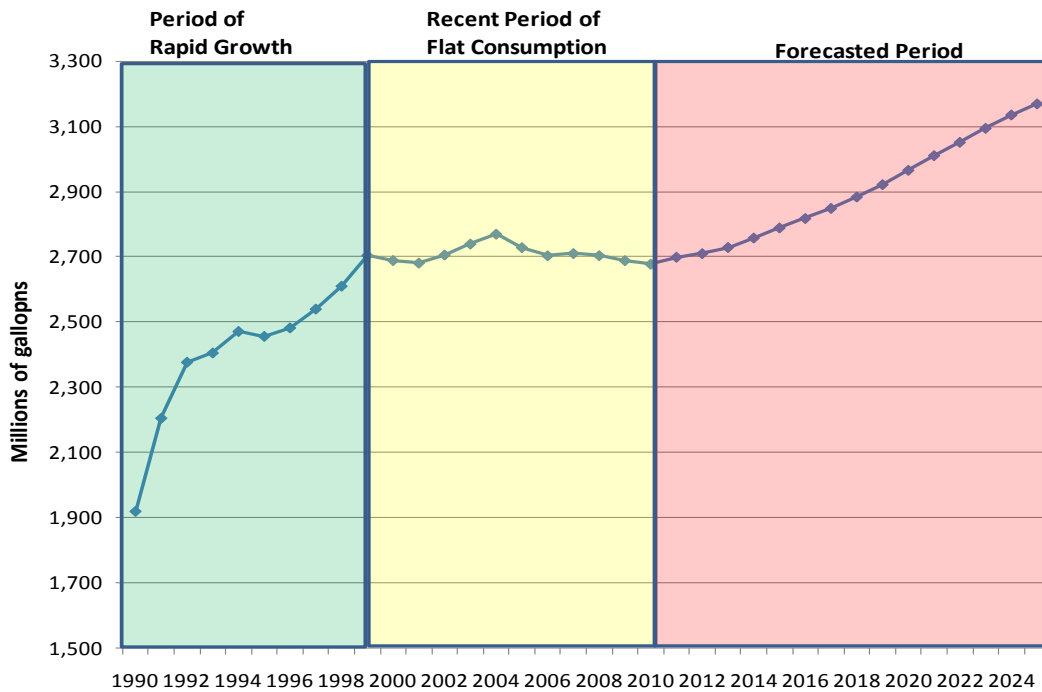


Figure 2 illustrates the different annual trends in gasoline consumption since 1990 along with the June 2010 forecast of gasoline consumption. From 1990-1999, there was moderate growth (avg. 4% per year) in gasoline consumption. Since 2000, gas consumption has been very flat at an average rate of -0.04% per year. During the recent recession, gas consumption has declined only minimally which is a contrast to the recent trend in diesel consumption. This chart also reveals a disconnect between the gasoline consumption forecast model results and recent history of gasoline consumption. Even though over the past 10 years gasoline consumption has been on average flat with nearly no growth, the current gasoline consumption forecast model is upward sloping. For the upcoming biennium (fiscal years 2011-13), the projected average annual growth rate is 0.7% per year. In the subsequent biennia, the annual growth rate is between 1-2%, with an average growth rate of 1.3%.

FIGURE 2. ANNUAL GASOLINE CONSUMPTION IN WASHINGTON SINCE 1990 PLUS SEPTEMBER 2010 FORECAST (MILLIONS OF GALLONS)



Components of OLD Gasoline Per Capita Consumption Forecast Model

WSDOT's old methodology for forecasting gasoline consumption uses a quarterly econometric forecast model for seasonally adjusted annualized gross fuel consumed per capita in gallons. The Washington gasoline forecast is derived from a regression model that estimates per capita gasoline consumption using independent variables of U.S. real gasoline prices, U.S. average light-duty fuel efficiency, a "dummy" variable that captures the impact of severe oil supply disruptions and driving age population (Pop Age ≥ 18 yrs). A log-log model is used with ordinary least squares regression.

- Equation – The equation for demand for gasoline sold in Washington per capita is defined as

$$\ln(G) = \alpha + \phi \ln(PG) + \delta \ln(MPG) + \varphi DGS + \varepsilon$$

Where

G = Quarterly Seasonally Adjusted Per Capita Gasoline Consumption (Seasonally Adjusted Gasoline/Driving Age Population (Pop Age ≥ 18 yrs)),

PG = 4-Quarter Moving Average Relative Price of Gasoline (Gasoline Index/Implicit Price Deflator for Personal Consumption),

MPG = Quarterly Average Light-duty Vehicle Fuel Efficiency for U.S.,

DGS = Quarterly Gas Non Price Rationing Dummy Variable.

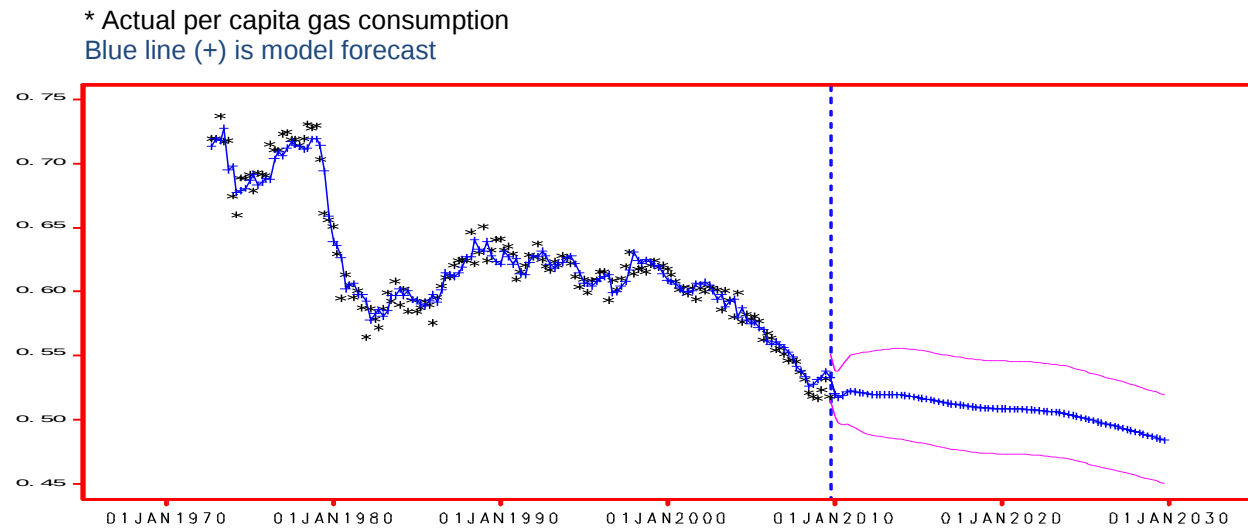
And

ε = Stochastic disturbance on quarterly Washington gasoline consumption.

The model also has first- and second-order autoregressive terms to correct for serial correlation.

Washington gasoline consumption has a strong positive correlation to the rate of growth of the driving age population and strong negative correlation to the real price of gasoline. The model's coefficient value for the refined US petroleum products price variable is -0.18, which in a log model is also the price elasticity of demand for gasoline. In Figure 3 below, the * depict the actual historical per capita gas consumption in gallons and the blue ++++ depict the forecasted trend line. Fuel efficiency also has a negative correlation to gasoline consumption with a coefficient of -0.27, but it has a larger standard error than the real price of gasoline. Fuel efficiency has also become less important since the variable has been relatively constant for the last 15 years. Real price is the most important driver of the gasoline consumption forecast model given relatively higher prices and price volatility in recent years, and higher prices projected for the future.

FIGURE 3. OLD GASOLINE PER CAPITA CONSUMPTION FORECAST MODEL HISTORY AND PROJECTIONS



Model Parameter	Estimate	Std. Error	T-stat	Prob.
Intercept	1.04	0.197	5.27	<0.0001
Gasprice Index/IPDC ratio (log)	-0.176	0.029	-6.03	<0.0001
Fuel efficiency(log)	-0.271	0.061	-4.41	<0.0001
AR1Lag1	0.410	0.080	5.27	<0.0001
AR1Lag2	0.315	0.081	3.88	0.0002
Dummy	-0.035	0.012	-2.95	0.0037
Adj. R ² =	0.96	RMSE =	0.011	
Schwarz Bayesian Criterion =	-1,326.4			

Model Results based on June 2010 economic variables

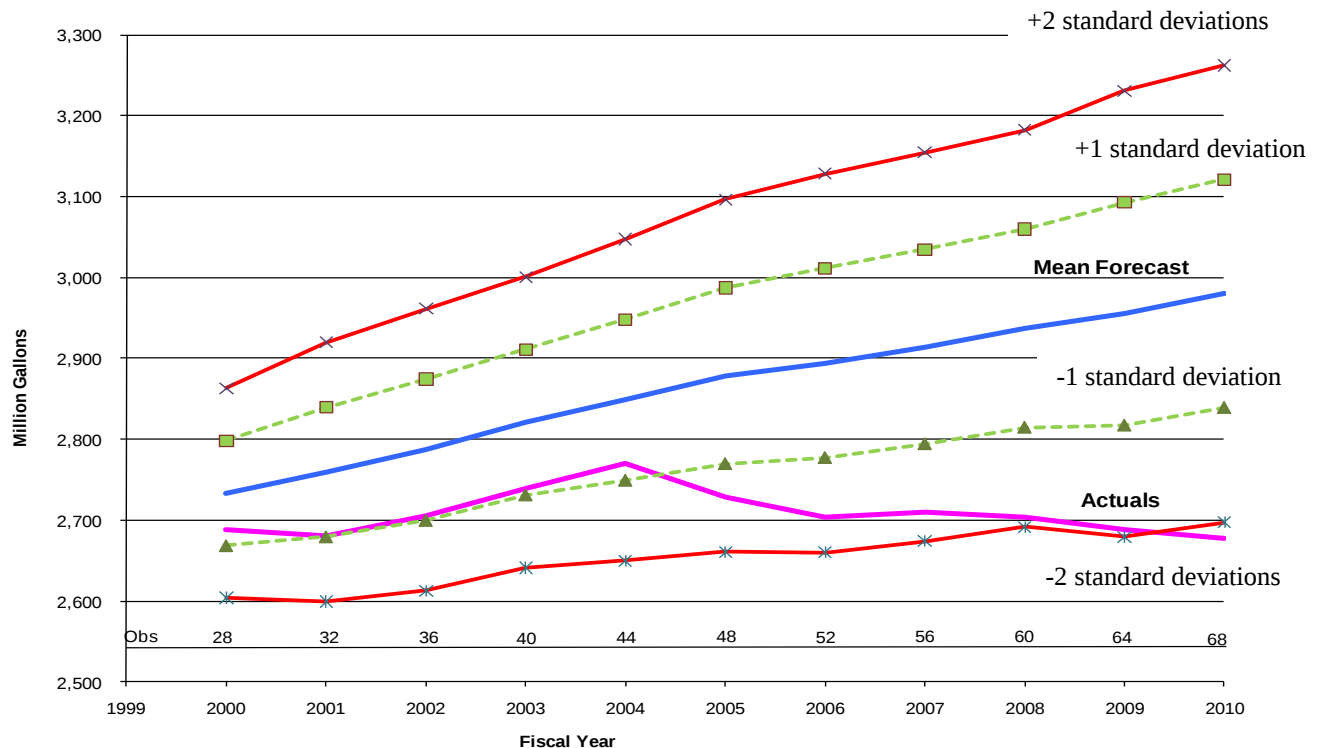
After further examination of the current gasoline forecast model results, white noise problems can be seen in lag 3 of the model results. White noise occurs in time series disturbances if the errors each period are

random; Problems with white noise means the regression model error terms are predictable and are related to past errors in a pattern for certain time periods.

Forecast Accuracy – Old Methodology

In the beginning of this forecast technical workgroup, WSDOT-Economic Analysis section analyzed the accuracy of the forecast methodology prior to April 2010. To determine the accuracy of the past forecasts, WSDOT-Economic Analysis compared gasoline consumption forecasts published by the Transportation Revenue Forecast Council (TRFC) from 1993 to 2010 with the actual fuel consumption as reported by the Washington State Office of the Treasurer. The results revealed that the forecasts were consistently overestimating gasoline consumed (Figure 4). The actual consumption for the years 2000-2010 was consistently below the mean forecast every year.

FIGURE 4. MEAN FORECAST (YEARS 2000-2010) FOR 17 YEARS OF FORECASTS COMPARED TO ACTUAL GASOLINE CONSUMED (MILLIONS OF GALLONS)

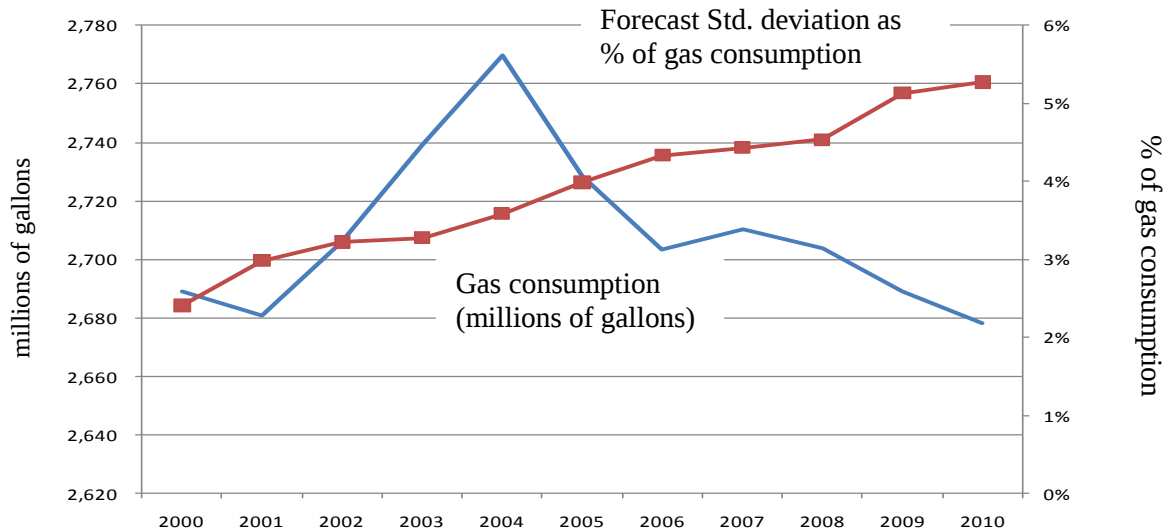


Results from 68 different quarterly fuel forecasts revealed that 147 forecasts, 28%, had percentage errors less than 3%, 100 forecasts, 19%, between 3 and 6%, and 280 forecasts, 53%, exceeded 6%. For the period 1993 to 2010, the forecast proved to be accurate up to 6 percent, 47% of the time. The majority of the time though, the gasoline consumption forecasts had an error of greater than 6%. For the period of 2000 to 2010, the forecast has been fairly accurate, plus or minus 3.6% for about 4 years out. The further out the forecast goes, the less reliable the projection becomes. It is interesting to note that in the past, the near term forecast was more accurate. Between 2000 and 2004, the absolute mean percent forecast error was 2.1% for up to 4 years out. From 2005 through 2010, the average absolute mean percent error was 4.8% for up to 4

4 years out. This reveals the decrease in the accuracy of the gasoline forecast model developed in recent years.

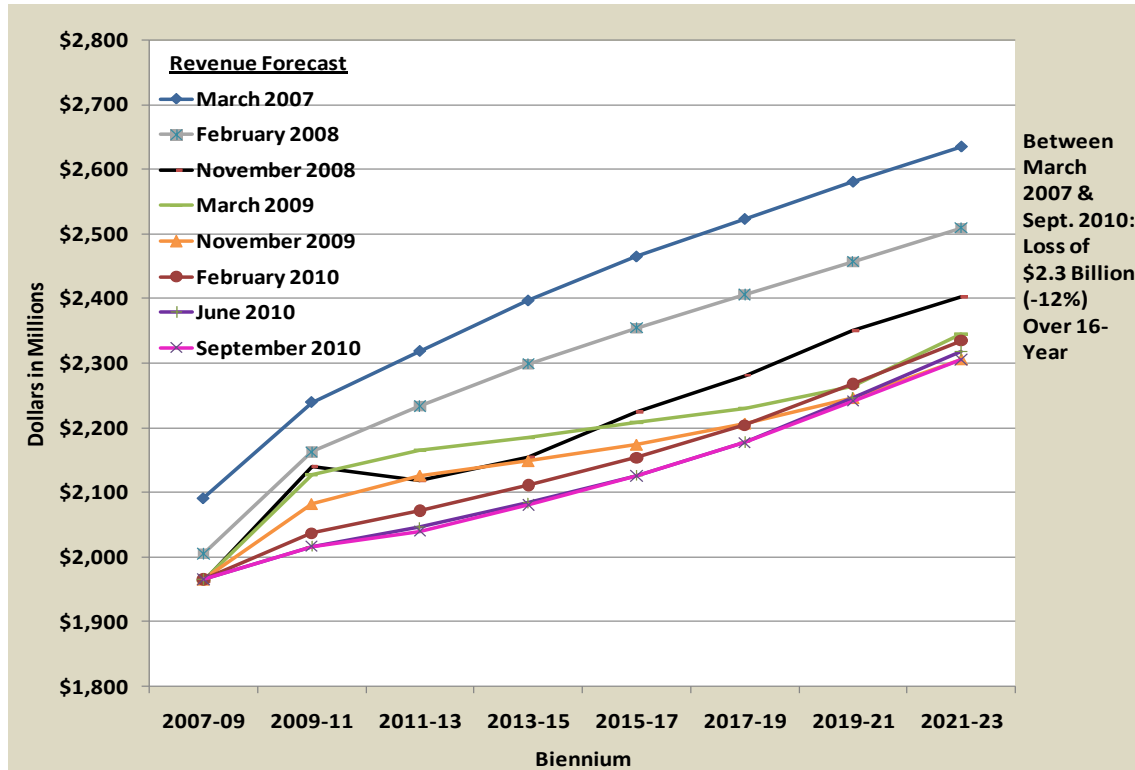
Figure 5 also reveals how the old gasoline consumption forecasts were getting less accurate in recent years. The gasoline model's forecast standard deviation as a percent of fuel consumption was climbing. In 2000, the forecast model's standard deviation as a percent of fuel consumption was 2.4%. Ten years later, the projection's standard deviation as a percent of gross fuel consumption had more than doubled to 5.3%. Gross fuel consumption in 2000 was at 2.69 billion gallons and by 2010 consumption had risen and fallen back down again to 2.68 billion gallons of gasoline.

FIGURE 5. COMPARISON OF FORECAST STANDARD DEVIATION AS PERCENTAGE OF GAS CONSUMPTION AND GROSS GAS CONSUMPTION (MILLIONS OF GALLONS) -YEARS 2000 THRU 2010



Even with the old gasoline forecast methodology, The Washington State Transportation Revenue Forecast Council forecasts of gasoline consumption have been declining. Figure 6 shows the quarterly revenue forecasts since March 2007. This graph shows that forecasts for gas consumption have been coming down consistently every quarterly forecast throughout the 16 year forecast horizon (2007-2023). Over this 16-year period, gasoline tax revenue projections have declined by \$2.3 billion; 12%, since the March 2007 forecast. Having more accurate fuel consumption forecasts will provide more realistic long-term forecasts, so that WSDOT is not be forced to bring down the gasoline tax revenue forecasts every quarter.

FIGURE 6. COMPARISON OF QUARTERLY GAS CONSUMPTION FORECASTS SINCE MARCH 2007



Trends in Washington's Diesel Consumption

Figure 7 shows Washington's historical quarterly seasonally adjusted and unadjusted diesel consumption since 1978. Quarterly gasoline consumption has some seasonal pattern but the seasonality has become more apparent since 2000. Prior to 2000, the seasonally adjusted and unadjusted quarterly diesel consumption estimates were not that different. In the last 10 years, the difference between unadjusted and adjusted diesel consumption estimates has grown. After examining the quarterly diesel consumption data since FY 2006, first quarter diesel consumption is typically the lowest of the year at a five year average of 23%. Diesel consumption rises from the first quarter until the third quarter which typically has the highest fuel consumption quarter at a five year average of 27%. Then diesel consumption declines slightly in the last quarter to 26% but this is not as low as in the first quarter of the year. This is similar to the gasoline trends discussed earlier but there is a larger variation between the highest and lowest diesel consumption levels.

Since 1978, Washington annualized diesel consumption has risen from 162 million gallons consumed in the first quarter of 1978 to 595 million gallons consumed in the second quarter for 2010. During the early 1980s when we had a smaller, less severe recession, there was also a dip in diesel consumption; however Washington state consumption recovered slowly. Between 1987 and mid 1990s, diesel consumption rose steadily. Since second quarter of 1996 through 2007, diesel consumption has been steadily rising. Since 2008, diesel consumption has been declining.

In the second quarter of 2010, diesel consumption is now down to nearly the second quarter 2003 consumption levels. The average growth rates of diesel consumption during the 1990s, was 7.2%. Since 2000, the average annual growth in diesel consumption has declined significantly to -0.1%. This recent period's negative growth rate for diesel consumption is primarily due to the last two years, 2009 and 2010, having such large declines in diesel consumption.

FIGURE 7. QUARTERLY NON-SEASONALLY ADJUSTED AND SEASONALLY ADJUSTED ANNUALIZED DIESEL CONSUMPTION IN WASHINGTON SINCE 1978 (MILLIONS OF GALLONS)

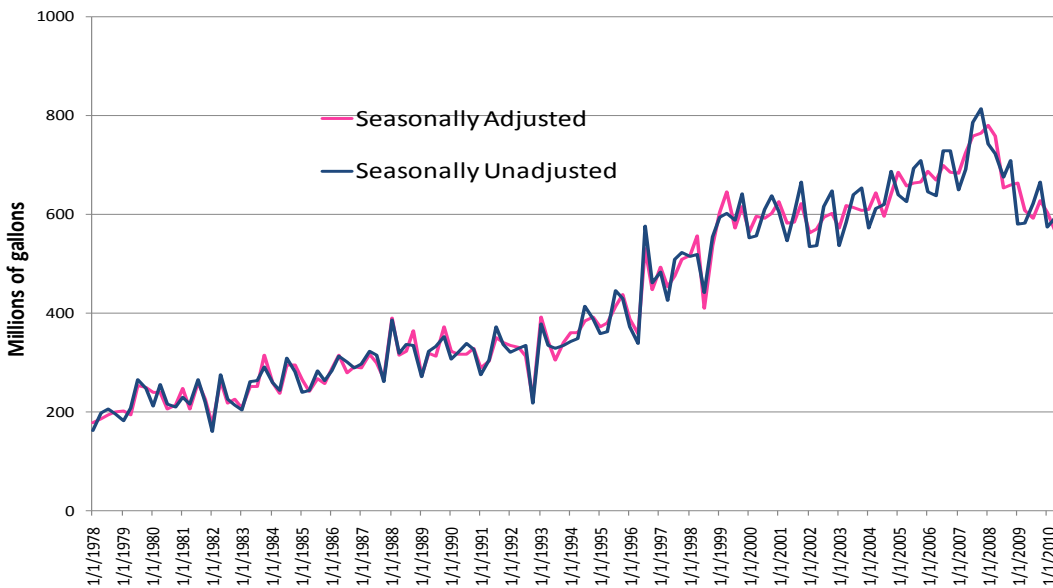
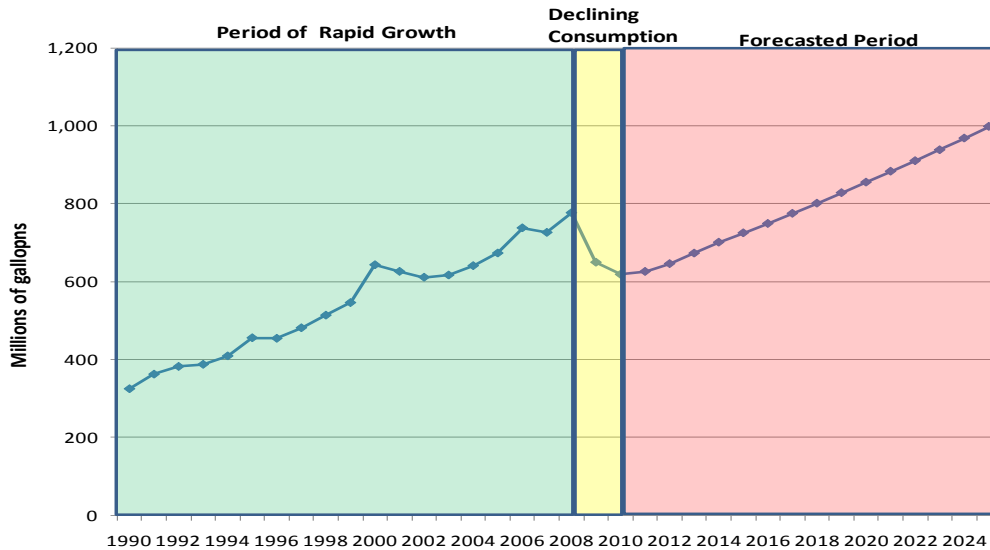


FIGURE 8. ANNUAL GASOLINE CONSUMPTION IN WASHINGTON SINCE 1990 PLUS SEPTEMBER 2010 FORECAST (MILLIONS OF GALLONS)



Components of OLD Diesel Consumption Forecast Model

WSDOT's old methodology for forecasting diesel consumption used a quarterly econometric forecast model for seasonally adjusted annualized gross fuel consumed in gallons. The Washington diesel forecast is derived from a model of seasonally adjusted diesel consumption as the dependent variable with an independent variable of Washington state real personal income. A linear ordinary least squares regression model is used.

Forecasting Methodology/Model

- The equation for demand for diesel sold in Washington is defined as

$$D = \alpha + \beta YP + \varepsilon$$

Where

D = Quarterly Seasonally Adjusted Diesel Consumption

YP = 4-Quarter Moving Average-Washington Real Personal Income

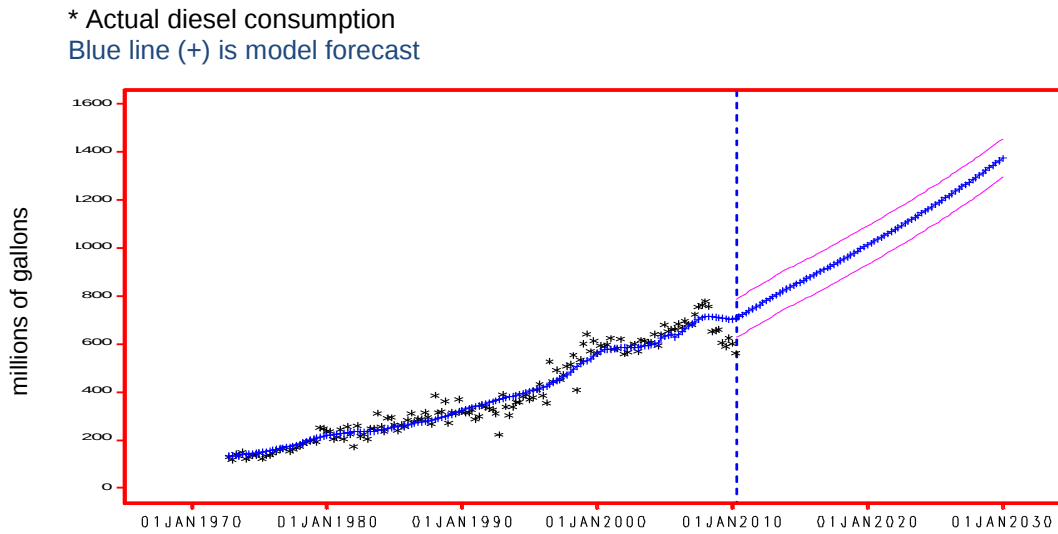
ε = Stochastic disturbance on quarterly Washington diesel consumption

The model does not have autoregressive terms to correct for serial correlation.

Washington diesel consumption has a strong positive correlation to the rate of Washington real personal income. The model's coefficient value for the income variable is 0.003 and the t-statistic was strong at 54.96. The overall fit of the model was high at an adjusted R squared of 0.953 and the mean square error was reasonably low at 40.8. As Figure 9 below reveals, in the quarters since the recent recession, this linear regression model has not predicted the decline in diesel consumption. The * depict the actual historical diesel consumption in gallons and the blue +++++ shows the forecasted trend line. Actuals have come in significantly below projections and

even the starting point for the lower bound of the confidence interval in 2010 is above the actual for the first quarter of 2010.

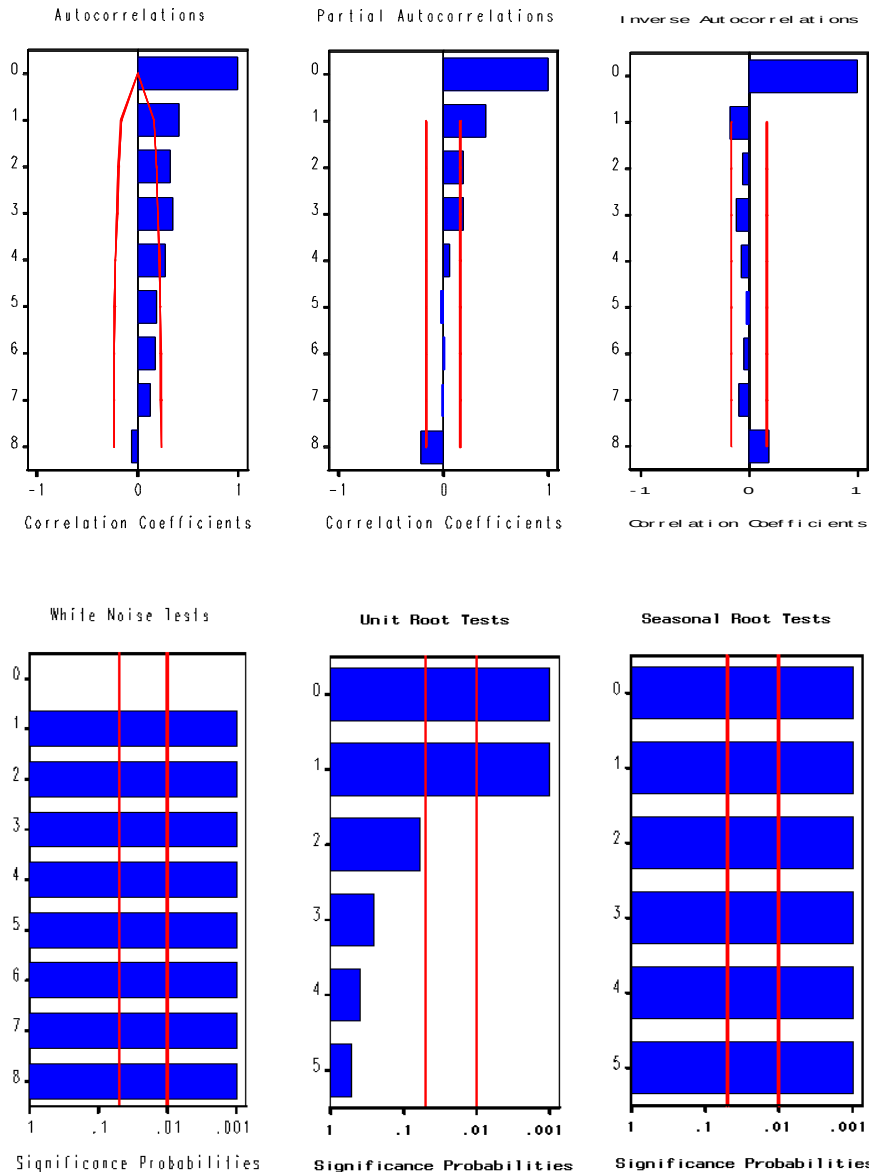
FIGURE 9. OLD DIESEL CONSUMPTION FORECAST MODEL HISTORY AND PROJECTIONS



Model Parameter	Estimate	Std. Error	T-stat	Prob.
Intercept	-66.303	8.9408	-7.416	< 0.0001
WA Personal Income (4-qtr moving average)	0.00303	0.000055	54.955	< 0.0001
Adj. R ² =	0.953	RMSE =	40.83	
Schwarz Bayesian Criterion =	1130.2			

Additional autocorrelation, white noise, unit root and seasonal root tests were performed on the existing diesel forecast regression model. The test results are shown in Figure 10 graphs. Autocorrelation problems exist for this model for the first through fourth lags. In addition, white noise problems exist in all lags and unit root problems begin in lag 2. Given the model's failure on various tests, alternative functional forms for the diesel model were considered and will be discussed in Chapter 2.

**FIGURE 10. OLD DIESEL CONSUMPTION FORECAST MODEL
AUTOCORRELATIONS, WHITE NOISE, UNIT ROOT AND SEASONAL ROOT
TESTS**



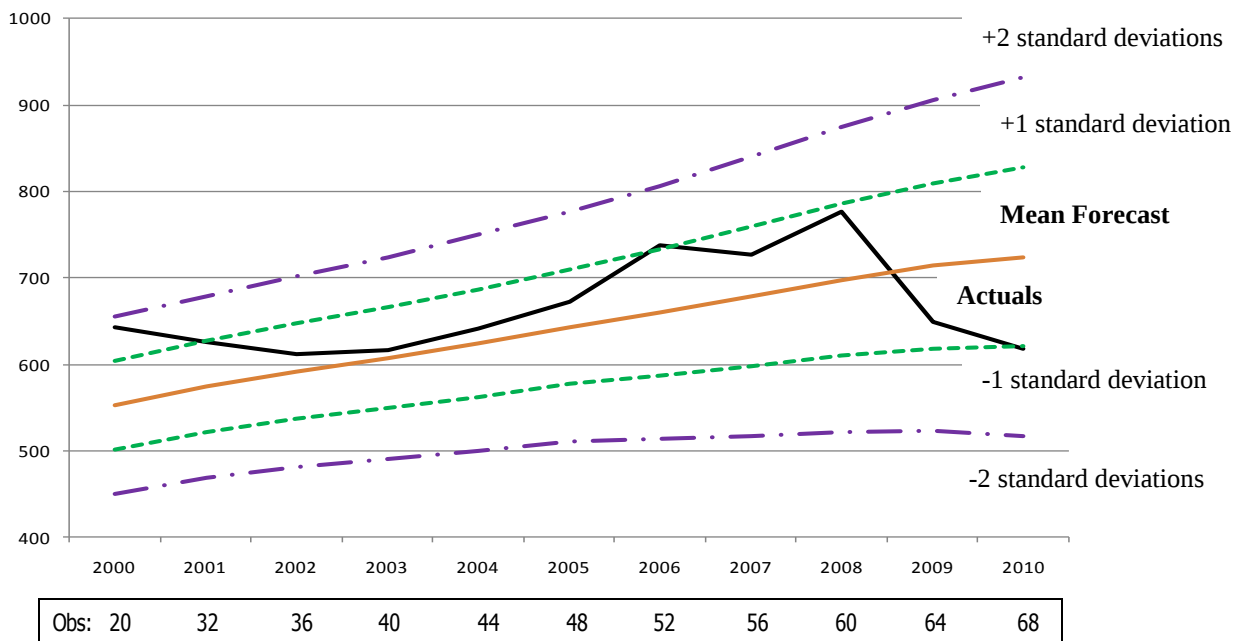
Forecast Accuracy – Old Methodology

In order to determine the accuracy of the past diesel consumption forecasts, WSDOT-Economic Analysis compared diesel consumption forecasts published by the Transportation Revenue Forecast Council (TRFC) from 1993 to 2010 with the actual fuel consumption as reported by the Washington State Office of the Treasurer. The results revealed that the forecasts were consistently underestimating diesel consumed, as seen in Figure 11, through 2008. However,

since the recent recession, the actual consumption for 2009 and 2010 was consistently below the mean forecast for those years.

The forecast study results from 68 different quarterly fuel consumption forecasts revealed that 100 forecasts, 19%, had percentage errors less than 3%. In 82 forecasts, 16%, had errors between 3 and 6%, and 346 forecasts, 65%, exceeded 6%. Between 1993 and 2010, the forecast was 6% accurate, 35% of the time. The majority of the time though, the diesel consumption forecasts had an error of greater than 6%. In the short term (out four years), the forecast between 2001 and 2010 was only marginally accurate, plus or minus 9.5%. This absolute mean percent forecast error is larger for the diesel consumption than the gasoline model.

FIGURE 11. ACCURACY OF DIESEL MODEL PROJECTIONS TO ACTUALS – FOR FORECASTS SINCE 1993



State Survey of Fuel Consumption Forecast Modeling

The work group was interested in surveying US states to get a sense of the fuel tax forecasting practices in other states. WSDOT contacted seventeen different states (Appendix I). This list of states also built upon an earlier survey performed during the 2006 transportation revenue forecast review. Of the seventeen states which WSDOT contacted, two of the states, California and Colorado, were in the process of developing new forecast models. Four states, Connecticut, North Carolina, Pennsylvania and West Virginia, did not have formal models but were examining other economic indicators (fuel prices, recent tax collections and population growth rates) to make their projections. Of the remaining eleven states, most use one or more key economic indicators in their forecast models: population, personal income, wages & salaries, GDP, fuel efficiency or employment. Most states with formal econometric fuel consumption forecast models included more than one economic variable in their models except for Texas which, used population to forecast gas consumption and gross state product to forecast diesel

Chapter 1: Background-Fuel Consumption Models

consumption. Most states had fuel efficiency, fuel prices or both in their gasoline consumption forecast model. Oregon was the only state with University of Michigan Consumer Sentiment as an independent variable in their gasoline forecast consumption model. Only four states, New York, Ohio, Texas and Vermont, had specific diesel consumption forecast models. The independent variables in diesel consumption forecast models were usually broader economic indicators like real national gross domestic product, gross state product, real personal income and population.

Indiana was one notable exception. Their forecast models projected motor vehicle registrations not fuel consumption. Indiana's regression models forecast the number of motor vehicle registrations in different categories and not fuel consumption. After estimating the number of vehicles in various categories, they then estimate fuel efficiency for all vehicles in the fleet. Finally, they derive a fuel consumption estimate by dividing vehicle miles traveled by the fleet fuel efficiency forecast.

Chapter 2: Independent Variables and Functional Forms Considered

Economic Activity Independent Variables

The key factors that determine the fuel consumed per capita in the state can be broken down into the number of vehicles on the roads, the miles per gallon of the vehicles on the roads and the miles traveled on each trip. Identifying key factors that can be used in an econometric model can be complex. Some of these factors are hard to predict (e.g., cultural shifts in driving habits, gas prices, fuel efficiency); some factors are random (e.g., weather conditions). Typically, economists only have a limited number of economic variables which can be used to predict relationships in regression models. The following independent variables were tested in econometric forecast models for statewide gasoline and diesel consumption.

- Gas and diesel prices (nominal and real)
 - percentage change in fuel prices
- Washington motor vehicle registrations
 - gas powered passenger cars and trucks and diesel trucks
- Washington non-farm employment
 - both US and WA industry specific employment in the manufacturing, trade, transportation, utilities and warehousing sectors
 - Washington unemployment rate
- Washington personal income
 - Washington personal income per capita
- Washington wages and salaries
- Total and driver aged population
- US average vehicle fleet fuel efficiency
- University of Michigan survey of Consumer Sentiment
- US industrial production
- US exports and imports
- US demand for petroleum products
- US and WA business income and profits

The independent variables considered by the workgroup fell into one of five broad categories: economic activity, population, motor vehicle registrations, fuel prices and efficiency, and consumer sentiment. The majority of these potential independent variables were highly correlated with fuel consumption.

Gasoline Consumption Forecast Model – Quarterly Models

One of the drawbacks to the old gasoline consumption per capita model was its heavy reliance on the real gas prices to predict future gasoline consumption. In the old model, the fuel price index and fuel efficiency are negatively correlated with gasoline consumption. Prior attempts to include other economic activity variables like personal income in the forecast model were not successful.

Chapter 2: Independent Variables and Functional Forms Considered

Personal Income

We hypothesized that Washington real personal income is positively correlated with gas consumption, so as more people are employed and personal income rises, people should increase miles driven and gas consumption should rise as well. The regression results revealed that when Washington real personal income is added to the current gas consumption per capita model with real gas prices, fuel efficiency and a dummy as independent variables, the income variable and fuel efficiency variable coefficients have the correct signs but they are insignificant in the model. If Washington personal income per capita is added to the regression model with fuel efficiency and the dummy variable, Washington personal income per capita and fuel efficiency have the correct sign, but they are insignificant at the 95% confidence level. An attempt was made to include wages and salaries in the regression model under the assumption that wages and salaries might be more closely aligned with gasoline consumption than other income components that are in personal income. Unfortunately, including wages and salaries into a gas consumption per capita model did not improve the regression model.

Regression models for total gas consumption were also examined, as an alternative to using gasoline consumption per capita. For these total consumption models, adding Washington real personal income to the model was an improvement over the per capita model, but the fuel efficiency variable still resulted in an insignificant variable and the incorrect sign. Figure 12 reveals the statistics on the regression model with Washington personal income, fuel efficiency and the dummy variables as the explanatory variables in the model. The insignificance of the fuel efficiency variable was a consistent problem in the modeling. Again using wages and salaries in the total gas consumption model did not improve the fit of the regression model.

FIGURE 12. GAS CONSUMPTION REGRESSION RESULTS FROM ADDING PERSONAL INCOME

Includes two autoregressive terms with lags 1 and 2

Model Parameter	Estimate	Std. Error	T-stat	Prob.
Intercept	0.0008	0.002	0.544	0.588
WA Personal Income	0.235	0.103	2.27	0.025
Fuel efficiency	0.050	0.139	0.356	0.723
Dummy	-0.028	0.013	-2.185	0.031
Adj. R^2 =	0.99	RMSE =	38.22	
Schwarz Bayesian Criterion =	1108.4			

Washington Employment

Washington employment was anticipated to be positively correlated with per capita consumption of gasoline because as more people are employed in the state, then they will drive more and consume more gasoline. Once the log of employment, fuel efficiency and the dummy variables were regressed on per capita gasoline consumption, then the employment variable had a negative

Chapter 2: Independent Variables and Functional Forms Considered

sign which was counter to economic logic and the variable was also insignificant. The fuel efficiency variable in that model was also insignificant. Adding logged Washington employment, fuel efficiency and a dummy variable to a model for forecasting total gasoline consumption resulted in improved results as shown in Figure 13. Log Washington employment has the correct sign and is significant in the regression but log fuel efficiency is not significant. Again, the insignificance of the fuel efficiency variable was a problem in the regression model.

FIGURE 13. GAS CONSUMPTION REGRESSION RESULTS FROM ADDING WASHINGTON EMPLOYMENT

Includes two autoregressive terms with lags 1 and 2

Model Parameter	Estimate	Std. Error	T-stat	Prob.
Intercept	3.670	0.443	8.29	< 0.0001
WA Employment (log)	0.544	0.096	5.64	< 0.0001
Fuel efficiency (log)	-0.032	0.136	-0.23	0.816
Dummy	-0.026	0.013	-2.03	0.044
Adj. R ² =	0.99	RMSE =	38.03	
Schwarz Bayesian Criterion =	1100			

Washington Population and Motor Vehicle Registrations

We anticipated that Washington population and motor vehicle registrations would be positively correlated with gasoline consumption. As the state population increases and motor vehicle registrations increase, then additional vehicles should be on the roadways and fuel consumption should rise. The results reveal that if population, fuel efficiency and the dummy variable are regressed against gasoline consumption, then total population is positively correlated and statistically significant. In contrast, fuel efficiency is negatively correlated with gasoline consumption but not significant in the model. White noise problems also exist in this regression model in lag 3. Overall, the results reveal that the regression models with population as the primary independent variable do not perform any better than the models with Washington personal income or employment.

Even though motor vehicle registrations have a close nexus with fuel consumption, this variable did not perform better than regression models with personal income or employment as the principal variables. When the log of motor vehicle registrations per capita, fuel efficiency and the dummy variables were used to forecast gasoline consumption per capita, total motor vehicle registrations had the correct sign but insignificant in the model. Fuel efficiency with motor vehicle registrations was significant with the correct sign. Total motor vehicle registrations were also regressed with fuel efficiency and the dummy variable on total gasoline consumption. That model resulted in a motor vehicle registrations variable that had the correct sign and was statistically significant in the model but the fuel efficiency variable had an incorrect positive sign and was insignificant in the model.

In addition to total motor vehicle registrations, gasoline only powered passenger cars and light trucks were also tested. These variables performed even poorer than total motor vehicle registrations. One reason for the poor performance of gas powered vehicle registrations in the quarterly regression models for gasoline consumption was because the quarterly distribution of vehicle registrations does not necessarily

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depict typical quarterly fuel consumption practices of residents. A disconnect exists between the month when a person registers his/her car and the monthly gasoline purchases.

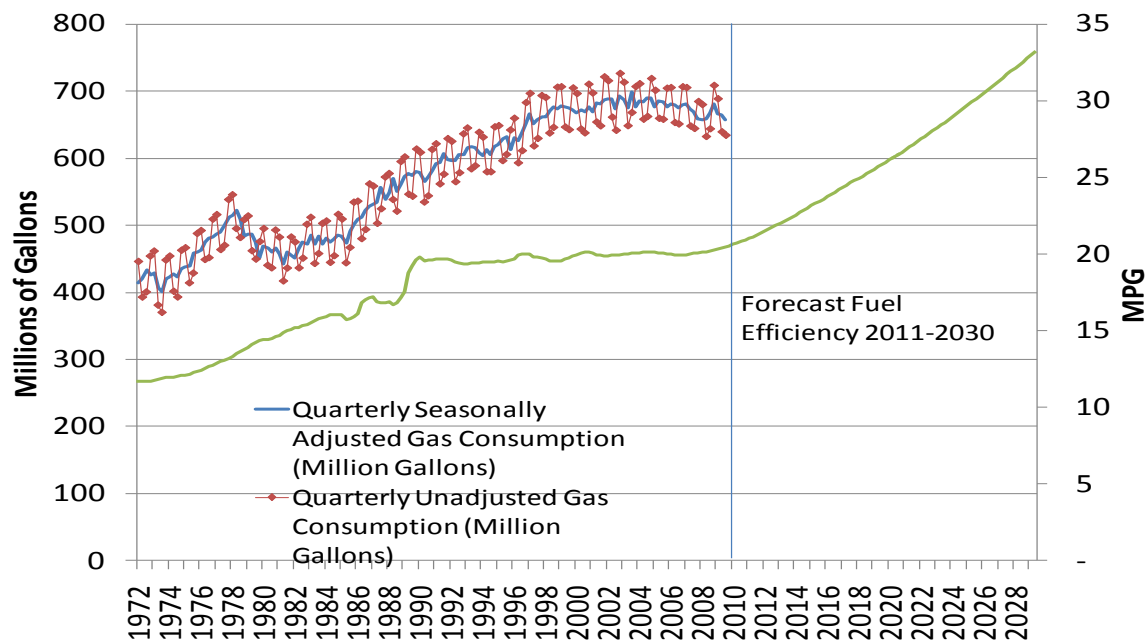
University of Michigan US Consumer Sentiment Variable

In the quarterly and annual gasoline consumption regression models, the University of Michigan US Consumer Sentiment variable was tested to see if it would be important in these models. We hypothesized that as US consumer sentiment increases, so would driving and fuel consumption. Essentially, as people feel confident about the outlook of the economy, because of more employment opportunities, rising wages and more travel is completed, then fuel consumption will rise as well. After including this variable in numerous regression models, the consumer sentiment variable was consistently insignificant compared to other economic activity variables and the composite fuel efficiency and gas price variable.

Composite Fuel Efficiency and Gas Price Variable

One consistent problem with alternative gas consumption forecast models is the lack of significance of the fuel efficiency variable with other economic activity explanatory variables. One of the problems with fitting the fuel efficiency past history to the gasoline consumption history is that fuel efficiency has not changed significantly. Gasoline consumption from 1970 rose quite substantially, but in the past 10 years, gasoline consumption has been flat and even declined slightly. Figure 14 shows the comparison of fuel

FIGURE 14. GAS CONSUMPTION AND FUEL EFFICIENCY TRENDS SINCE 1972



efficiency historical trends versus gasoline consumption. As this figure reveals, fuel efficiency grew slowly between 1972 and 1988. Since 1990, fuel efficiency has been flat. Between the first quarter of 1990 and 2010, average US fuel efficiency rose from an average of 18.74 miles per gallon to 20.39 miles per gallon, a little under 1.7 miles per gallon or 9%, in twenty years. In contrast, since 1990, total gasoline consumption grew 15%. The forecast for fuel efficiency is projected to grow faster than any historical period since the 1970s. Even though the future fuel efficiency changes are anticipated to have a large damping effect on fuel consumption, our history of fuel efficiency has never experienced that type of

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growth or negative influence on fuel consumption. This poses difficulties in using this variable to project significant changes to the fuel consumption forecast in future.

To overcome these complications, a composite fuel efficiency and Washington gas price was developed by multiplying the fuel efficiency and Washington gas prices together. This composite variable could be created because both fuel efficiency and gas prices are anticipated to have a negative impact on gasoline consumption and will have the same directional influence on the dependent variable. Additional regression models were tested with the composite variable of fuel efficiency and gas prices. All of the previously attempted economic activity variables (Washington personal income and employment) and population and motor vehicle registrations were evaluated with the composite variable. The quarterly regression results reveal that for a quarterly total gasoline consumption model, all four economic variables (WA personal income, employment, population and motor vehicle registrations) had the correct anticipated positive sign and significance in separate regression models with the gas price and fuel efficiency composite variable. The adjusted R squared of each of these regression models was 0.99 so it was very high. Root mean square error (MSE) values also were good, ranging from a high of 44 for the model with log motor vehicle registrations and the composite variable to the lowest MSE of 35 for the regression model with log Washington employment and the composite variable. When comparing root mean square errors (RMSE) for regression models, the model with the lowest RMSE is best. In the quarterly total gas consumption model, the log Washington employment and composite variable is the best regression model since it has the lowest RMSE.

Gasoline Consumption Forecast Model – Truncated Models

In addition to examining the quarterly gasoline consumption models with historical data back to 1973, the work group also tested truncated quarterly gasoline regression models. This was important because in examining gasoline consumption over time, as shown in Figure 2, there has been a very flat and even declining gasoline consumption period since fiscal year 2000. It is critical to see how much of an impact running regression models on the consumption data since 2000 would have on future gasoline consumption projections.

First, the old per capita consumption model independent variables were examined on truncated data since fiscal year 2000. The results indicate that the gas price index, adjusted by the price deflator, were still negative and significant in the model but that fuel efficiency was insignificant. The projections from the old model were significantly lower than using the longer term history for the variables back to 1973.

In examining Washington personal income and the composite variable of fuel efficiency and gas prices, the results for the truncated gasoline per capita consumption model reveal that the composite variable is significant and negatively correlated but the first difference of the Washington personal income variable was positive but insignificant in this regression model. The composite variable in the per capita regression model had the correct sign but was insignificant. This same result was found when the change in total population along with the composite fuel efficiency and price variable were regressed on total gasoline consumption. The change in population was positively correlated but insignificant in the per capita regression model and the composite variable also had the correct sign but insignificant. Motor vehicle registrations along with the composite variable for fuel efficiency and gas prices were regressed on per capita gasoline consumption. The composite variable of fuel efficiency and gas prices was negative and significant in the model but the registration variable was negative and not statistically significant at the 95% confidence level. Overall, the change in motor vehicle registrations with the composite variable was a pretty good model for the truncated history of gasoline consumption per capita. The best model for the per capita truncated history included the change in Washington employment along with the composite fuel efficiency and gas prices variable. This per capita consumption regression model had both independent variables significant and the anticipated sign in the model. The overall statistics in the model

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were not as high with an adjusted R squared of 0.905, as opposed to 0.99 in other models. Motor vehicle registrations were also added to the regression model of the change in Washington employment and the composite variable. Even though the Washington employment and composite variable were significant, motor vehicle registrations were insignificant in the regression model. Therefore, the best model for the per capita truncated history included the change in Washington employment along with the composite fuel efficiency and gas prices variable.

FIGURE 15. TRUNCATED PER CAPITA GAS CONSUMPTION REGRESSION RESULTS: BEST MODEL

Includes an autoregressive term with lags 3

Model Parameter	Estimate	Std. Error	T-stat	Prob.
Intercept	0.601	0.030	20.32	< 0.0001
WA Employment (first difference)	0.0003	0.0001	3.41	0.0015
Fuel efficiency*gas prices	-0.0008	0.0002	-3.32	0.0019
Adj. R ² =	0.905	RMSE =	0.0099	
Schwarz Bayesian Criterion =	-390			

The variable of a change in gasoline powered vehicles along with the composite variable were included in a truncated per capita gas consumption model. Both independent variables in this model were significant and of the anticipated sign. The change in the gasoline powered vehicles was also added to a truncated regression model with change in Washington employment and the composite variable. The model results did produce the appropriate sign for each variable and statistically significant variables. The overall regression model statistics were not an improvement over the model with the change in Washington employment and the composite variable or the change in passenger vehicle registrations and the composite variable.

Total quarterly gasoline consumption truncated models were developed as well as the per capita gasoline consumption models and the results revealed that most of the total gasoline consumption truncated models did not have better results than the quarterly per capita gasoline consumption models. For example, when quarterly Washington employment and the composite fuel efficiency and gas prices were regressed on the truncated data for total gasoline consumption, the composite variable was just barely statistically significant at the 95% confidence level but the Washington employment was not statistically significant. The overall fit of this total consumption truncated regression model was significantly worse with an adjusted R squared of 0.36.

The three best quarterly regression models included the following economic variables with the composite variable for fuel efficiency and gas prices:

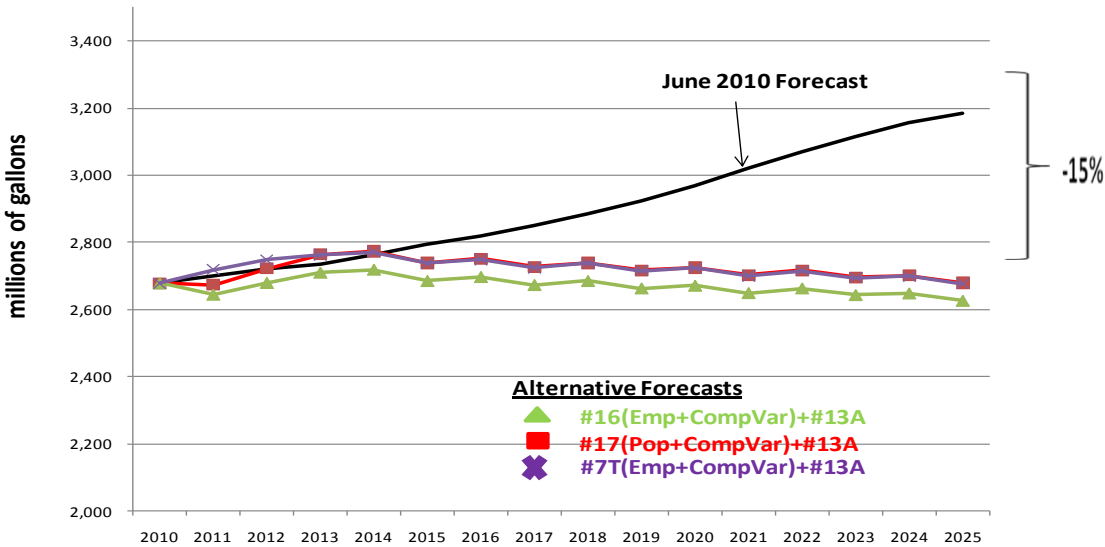
1. Washington employment – long term historical model
2. Washington population – long term historical model
3. Washington employment– truncated model

All three of these quarterly regression models produced very similar forecasts, (Figure 16). In the near term, all three best annual models produced forecasts nearly comparable to the current law forecast in June 2010. The quarterly models with Washington employment and the composite variable and the Washington population and the composite variable are both slightly lower than the current law forecast in

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fiscal years 2011 - 2012. From fiscal year 2013 and beyond, the historical long term model with Washington employment and population with the composite variable produced nearly identical forecasts as the quarterly truncated model with Washington employment and the composite variable. In the best quarterly models selected, truncating the data or not is not a critical factor in the projections. Similar forecasts are found in both the truncated and non-truncated data models. In the long-term, after fiscal year 2014, the alternative quarterly forecasts produce lower projections than the June forecast. The largest difference between the lowest forecast and the current forecast by fiscal year 2025 is a decline of 15%.

FIGURE 16. COMPARISON OF BEST QUARTERLY GASOLINE CONSUMPTION FORECAST MODELS



Gasoline Consumption Forecast Model – Annual Models

The workgroup developed annual regression models to determine the forecast differences between annual and quarterly forecast models. In addition, this was a concern expressed by the 2006 OFM Transportation Forecast Review group. They noted the lack of a long-term elasticity for gas prices as one drawback to the old quarterly gas consumption model. To address this, WSDOT examined annual regression models for data starting in 1973.

FIGURE 17. ANNUAL TOTAL GAS CONSUMPTION REGRESSION RESULTS: WA EMPLOYMENT

Includes autoregressive terms with lags 1 and 2 and a moving average term of lag 2

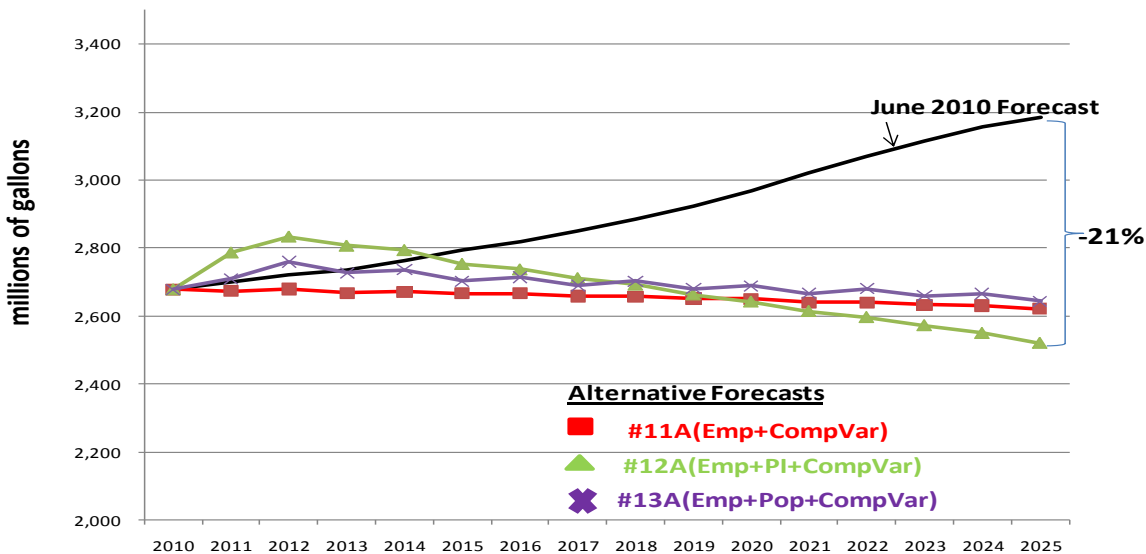
Model Parameters	Estimate	Std. Error	T-stat	Prob.
Intercept	7.914	0.432	18.33	
WA Employment (log first difference)	0.467	0.175	2.67	
Fuel efficiency*gas prices (lag 1)	-0.093	0.0267	-3.49	
Adj. R ² =	0.979	RMSE =	46.01	
Schwarz Bayesian Criterion =	289.4			

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One of the better annual regression models developed used the change in the log of Washington employment along with the composite fuel efficiency and gas prices. Both independent variables were of the anticipated sign and were statistically significant in the model (Figure 17).

Other independent economic variables like Washington personal income were also tested in the regression model (Figure 18). Adding the change in Washington personal income did not provide statistically significant results. On the other hand, adding the change in population to the regression model did yield good results with the change in population variable being statistically significant, along with the change in Washington employment and the composite variable. This proved to be the best overall annual gasoline consumption model due to including 3 independent variables: one economic activity variable (Washington employment), an indicator of state population and the combined effect of gas prices and fuel efficiency changes.

FIGURE 18. COMPARISON OF THE BEST ANNUAL TOTAL GAS CONSUMPTION REGRESSION RESULTS



Other variables were also tested in the annual regression models similarly to the quarterly regression models. The variable of gas powered vehicles was added to the regression model. This variable was positively correlated but not statistically significant at the 95% confidence level in the regression model. University of Michigan consumer sentiment was also tested which proved to be insignificant in all cases.

The three best annual regression models included the following economic variables with the composite variable for fuel efficiency and gas prices:

1. Washington employment
2. Washington employment and personal income
3. Washington employment and population

All three of these annual regression models produced very similar forecasts, (Figure 18). In the near term, two of the three best annual models² produced slightly higher forecasts than the current law forecast in

² Regression models with Washington employment, composite variable for fuel efficiency times gas prices and Washington personal income and a model with Washington employment, composite variable for fuel efficiency times gas prices and Washington population

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June 2010. In the long-term, after fiscal year 2014 and beyond, the alternative annual forecasts produce lower projections than the June 2010 forecast. The largest difference between the lowest alternative forecast and the current law forecast by fiscal year 2025 is a decline of 21%.

The best annual gasoline consumption model was the regression model with Washington non-farm employment with Washington population and the composite variable of gas prices and fuel efficiency.

Diesel Consumption Forecast Model – Quarterly Models

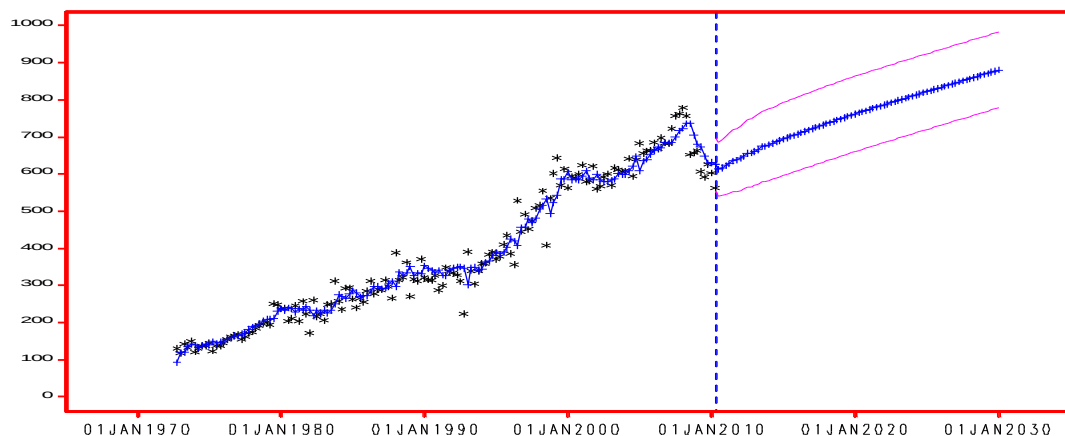
Some of the drawbacks to the old diesel consumption model are its heavy reliance on Washington real personal income, its linear functional form, and its lack of autoregressive terms and the inclusion of a moving average term for the independent variable to predict future diesel consumption. In the old model, the diesel consumption forecast depends solely on a one year moving average of Washington personal income where real personal income is positively correlated with diesel consumption. One of the drawbacks to using a moving average of Washington real personal income is that it delays picking up the downturns and upturns in real personal income when making future projections. In the recent recession, this model was very slow to respond to the economic downturn in 2009 and 2010 and consequently, the model projections over the last two years have consistently overestimated actual diesel consumption.

Functional Form Modifications

The work group's review of the diesel consumption model also considered alternative functional forms in addition to linear models for the new forecasts.

One of the problems with the old diesel consumption model was that it displayed non-randomness or white noise problems for all lag periods. In addition, autocorrelation problems existed in lags 1 thru 4. A log – log diesel consumption model was tested with the moving average of personal income along with an autoregressive and a moving average term. Figure 19 shows the effects of changing the functional form to a log-log model from a linear model and adding autoregressive and moving average term. This revised log-log diesel model eliminated the autocorrelation and white noise problems in subsequent time periods.

FIGURE 19. LOG –LOG DIESEL CONSUMPTION MODEL: AR(1), AR(2), MA(2) AND PERSONAL INCOME (4 QTR MOVING AVG)



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Includes autoregressive terms with lags 1 and 2 and a moving average term of lag 2

Model Parameters	Estimate	Std. Error	T-stat	Prob.
Intercept	-4337	459.01	-9.45	<0.0001
WA Personal Income (4 qtr MA)	398.93	38.76	10.29	<0.0001
Adj. R ² =	0.962	RMSE =	36.09	
Schwarz Bayesian Criterion =	1108.1			

Choosing the appropriate economic variables for the diesel consumption model is similar to the gasoline consumption forecasting process, but the choice of variables appropriate for this model are not exactly the same. Since the primary source of diesel consumption is commercial trucking, some of the economic indicators tested in the alternative diesel consumption forecast models were trade and warehousing related. The economic intuition is that as more goods are manufactured or imported and exported from Washington state, trucking demand and diesel consumption will rise. Some indicators of Washington state and U.S. trade and production may be effective in predicting future trucking demand and diesel consumption.

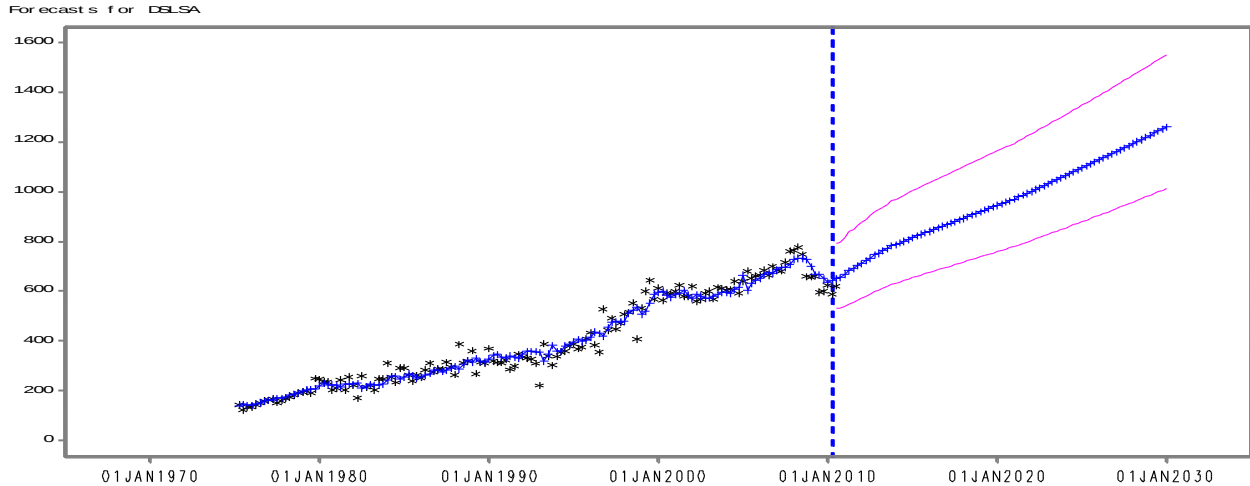
Personal Income and Its Components

As Figure 19 illustrates, personal income does a fine job in predicting future diesel consumption, as it is positively correlated with diesel consumption and significant in the regression model. The regression model with Washington real personal income as the explanatory variable does not need to have a four quarter moving average in order for Washington real personal income to be significant in the regression model. Wages and salaries can also be used in a diesel consumption forecast model, as it performed well but the overall statistics of the regression model were not any better than including real personal income. One drawback to Washington personal income is that it is a broad measure that does not reflect specifically the trade or transport sectors and it includes all types of income besides wages and salaries. One advantage of real personal income is that since it is a broad measure, it does show the trends in overall production in Washington state.

Washington Employment

As with the gasoline consumption forecast model, Washington non-farm employment did well in the forecast regression models for diesel consumption. Washington employment in the trade transportation and utilities sectors performed even better for the diesel consumption forecast model. Washington employment in the manufacturing sector did not perform as well in the diesel consumption forecast model as Washington employment in the trade transportation and utilities sectors. Washington employment in the transportation and warehousing sectors also produced reasonable regression results for diesel consumption forecasts but was not as good as using Washington employment in the trade, transportation and utilities sectors. Using Washington employment in the trade, transportation and utilities sectors along with other economic variables like Washington personal income, population and exports was also successful in the diesel forecast models. Figure 20 presents the diesel consumption regression model with both Washington employment in the trade, transportation and utilities sectors (TTU) and WA real personal income. Both independent variables are the appropriate sign and statistically significant.

FIGURE 20. LOG –LOG DIESEL CONSUMPTION MODEL: AR(1), AR(2) AND WASHINGTON EMPLOYMENT _ TTU AND PERSONAL INCOME



Includes autoregressive terms with lags 1 and 2

Model Parameters	Estimate	Std. Error	T-stat	Prob.
Intercept	-7.88	0.52	-15.25	<0.0001
WA Emp_TTU (log)	0.60	0.25	2.36	0.019
WA Personal Income (log)	0.86	0.16	5.54	<0.0001
Adj. R ² =	0.959	RMSE =	36.55	
Schwarz Bayesian Criterion =	1046.8			

Washington Population and Motor Vehicle Registrations

Washington population works well as an independent variable in the diesel consumption forecast model. It also works well with Washington employment in the trade, transportation and utilities sectors as an independent variable. Using population with Washington employment in the trade, transportation and utilities sectors produces very similar results as the forecast model with Washington employment in the trade, transportation and utilities sectors and Washington real personal income. For example the root mean square error for the forecast model with population with Washington employment in the trade, transportation and utilities sectors is 36.8 versus 36.5 for the regression model with real personal income.

A quarterly log-log regression model with diesel powered truck registrations as the primary explanatory variable was tested. These results show little significance between diesel truck registrations and diesel consumption in the quarterly forecast model. Given that the diesel powered truck registrations do not come in consistently with the consumption of diesel, the truck registrations did not prove to be an important explanatory variable in the forecast model. Diesel powered truck registrations were also tested in the annual diesel consumption forecast model but the variable was not as effective an explanatory variable as other economic variables. For the log-log annual diesel consumption model with diesel

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powered truck registrations, the overall adjusted R squared is 0.79, which is significantly less than other regression model with adjusted R squared of at least 0.95.

US Corporate Profits and Washington Business Income Variables

It is anticipated that US corporate profits before taxes or Washington business income is positively correlated with diesel consumption. Once the economy and private businesses are thriving, then additional demand for trucking will be needed and diesel consumption will rise. The US corporate profits would capture trucking demand outside Washington. In the quarterly diesel consumption model, adding US corporate profits to Washington employment in the trade, transportation and utilities sectors produced reasonable results. US corporate profit was positively correlated with diesel consumption and statistically significant. One drawback to this economic indicator is that it is so broad that it is not clear what the variable is measuring. There is little nexus of this variable with the trucking industry or Washington state. In the annual diesel consumption models, the variable of US corporate profits was not statistically significant in models.

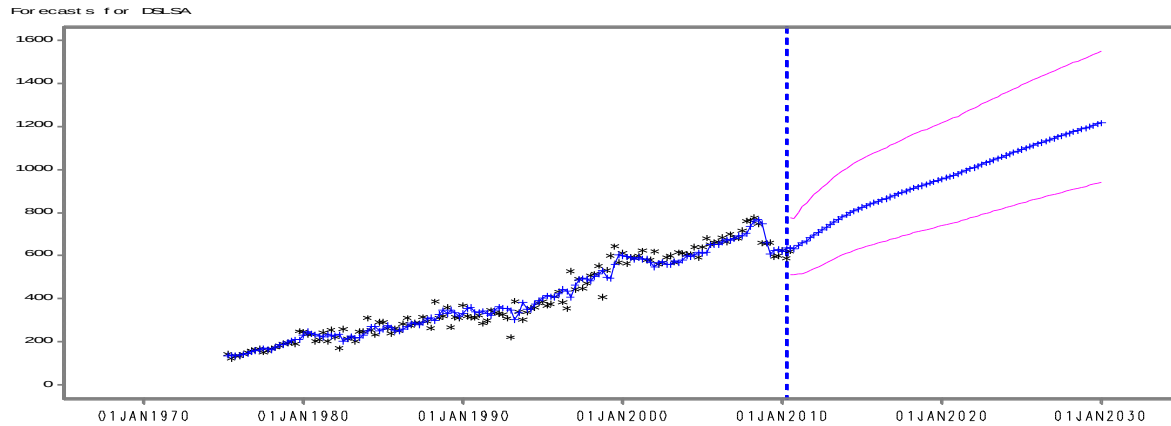
Washington taxable business income was also tested in a quarterly log-log regression model with Washington employment in the trade, transportation and utilities sectors. The Washington taxable business income was positively correlated with diesel consumption but the variable was not statistically significant at the 95% confidence level. Even though Washington taxable business income is a closer nexus to business activity in Washington state, it does not represent gross business income in the state. Since this variable is taxable business income, it only reflects the business income after net operating losses and many other exemptions which are allowed in the business and occupation tax in law. Since this variable does not reflect all business activities in Washington, using Washington taxable income is not the preferred independent variable in the diesel consumption model to represent business activities.

US Exports and Imports

Like US corporate profits, it is anticipated that US exports would be positively correlated with diesel consumption. As exports grow, demand for trucking and diesel consumption would also increase. When US exports along with Washington employment in the trade, transportation and utilities sectors are regressed in a quarterly diesel consumption model, both independent variables are positively correlated and significant, (Figure 21). One drawback to using US exports is that the regression model would be heavily weighted toward the trade sector since the Washington employment variable is specific for the trade, transportation and utilities sector. This could be a problem since much of the diesel consumed in Washington is in the retail sector.

In an annual diesel consumption model with US exports and Washington employment in the trade, transportation and utilities sectors, the results also showed positive and significant statistics for these independent variables.

FIGURE 21. LOG –LOG DIESEL CONSUMPTION MODEL: AR(1), AR(2) AND WA EMPLOYMENT _ TTU AND US EXPORTS



Includes autoregressive terms with lags 1 and 2

Model Parameters	Estimate	Std. Error	T-stat	Prob.
Intercept	-2.098	1.663	-1.261	0.209
WA Emp_TTU (log)	1.011	0.401	2.520	0.0129
US Exports (log)	0.315	0.131	2.399	0.0178
Adj. R ² =	0.956	RMSE =	37.77	
Schwarz Bayesian Criterion =	1056.1			

US Industrial Production and US Demand For Fuels

US industrial production was tested in the diesel consumption regression models. It was positively correlated and significant in regression models.

US retail demand for petroleum products was positively correlated but just barely statistically significant in diesel regression models. When US retail demand for petroleum products was added with other economic variables, the US retail demand for fuels variable was not statistically significant.

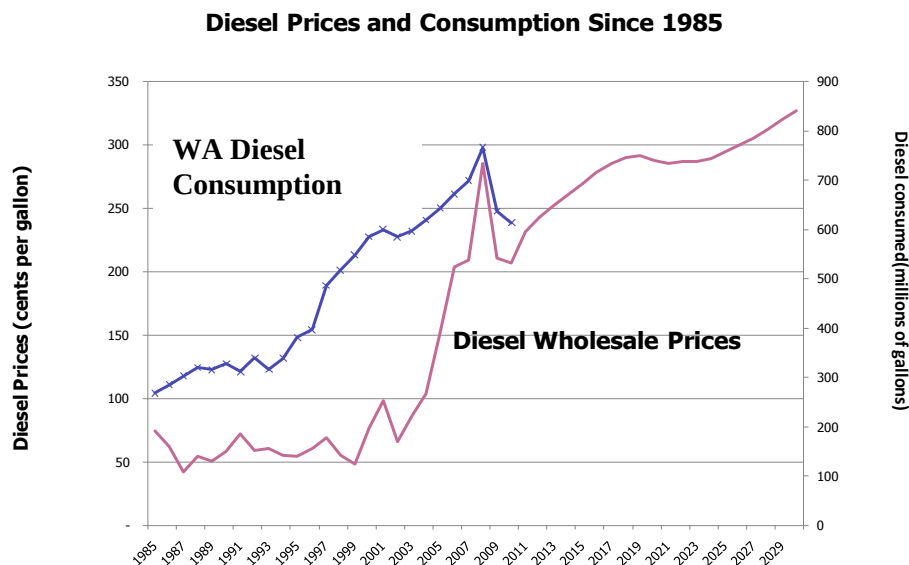
Michigan Consumer Sentiment Variable

In the quarterly and annual diesel consumption regression models, the University of Michigan Consumer Sentiment variable was tested to see if it would be important in these models. It was anticipated that as consumer sentiment increased, so would industrial production and retail sales driving up trucking demand and diesel consumption in the state. As more people feel good about the outlook of the economy, they will spend more, increasing retail sales and demand for goods and trucking to get the goods to the stores. This would lead to higher diesel consumption as well. After including this variable in numerous regression models, the consumer sentiment variable was consistently insignificant in the models compared to other economic activity variables in the diesel consumption forecast models.

Diesel Prices

Washington diesel prices were tested in the quarterly diesel consumption forecast models. Adding diesel prices to a log-log regression model with Washington employment in the trade, transportation and utilities sectors was negatively correlated as anticipated, but insignificant in the model. After examining the trend in diesel prices with diesel consumption, one can see that historically, diesel prices have risen over the same time period as diesel consumption has grown. In the data, the negative correlation between higher diesel prices leading to lower diesel consumption is not readily apparent. Therefore, it is not surprising that diesel prices are insignificant in the forecast model. The same result occurred in the annual regression models when diesel prices were added.

FIGURE 22. TRENDS IN DIESEL PRICES AND DIESEL CONSUMPTION SINCE 1985



Diesel Consumption Forecast Model – Annual Models

The workgroup also developed an annual regression model to determine the forecast differences between annual and quarterly forecast models. The same economic variables tested in the quarterly diesel consumption models were also run on annual diesel consumption data. The results between the annual and quarterly diesel consumption models were quite similar. The three best annual log-log regression models included the following economic variables with the Washington employment in the trade, transportation and utilities sectors:

1. Washington employment in the trade, transportation and utilities sectors and Washington personal income
2. Washington employment in the trade, transportation and utilities sectors and US exports and imports
3. Washington employment in the transportation and warehousing sectors and US exports and imports

All three of these annual regression models produced very similar forecasts, (Figure 23). The regression models of Washington employment of trade, transportation and utilities with imports/exports and the

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model of Washington employment of trade, transportation and utilities with Washington personal income produced very similar forecasts. The regression model of Washington employment of transportation and warehousing sectors with US imports/exports produced higher forecasts than the other two best models. All three of these diesel consumption forecast models produced forecasts above the current law September forecast throughout most of the forecast horizon.

The best alternative annual diesel consumption model is a log-log model of Washington employment of trade, transportation and utilities with Washington personal income. Figure 24 reveals the statistics from the best alternative annual diesel consumption forecast model.

FIGURE 23. COMPARISON OF THE BEST ALTERNATIVE ANNUAL DIESEL CONSUMPTION MODELS

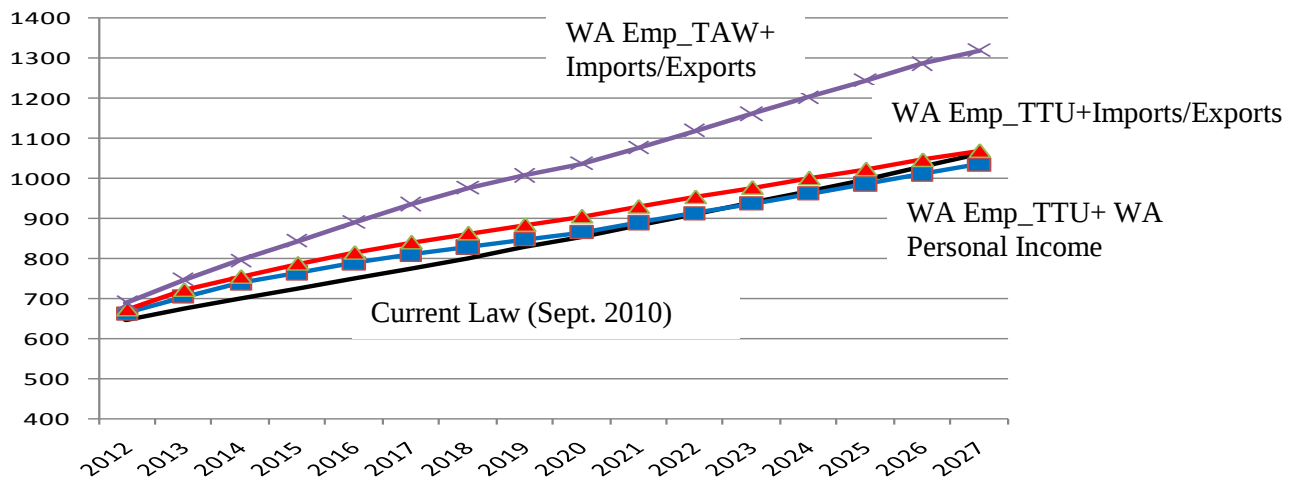


FIGURE 24. BEST ANNUAL DIESEL CONSUMPTION REGRESSION RESULTS: WA EMPLOYMENT_TTU AND WASHINGTON PERSONAL INCOME

Includes autoregressive terms with lags 1 and 2

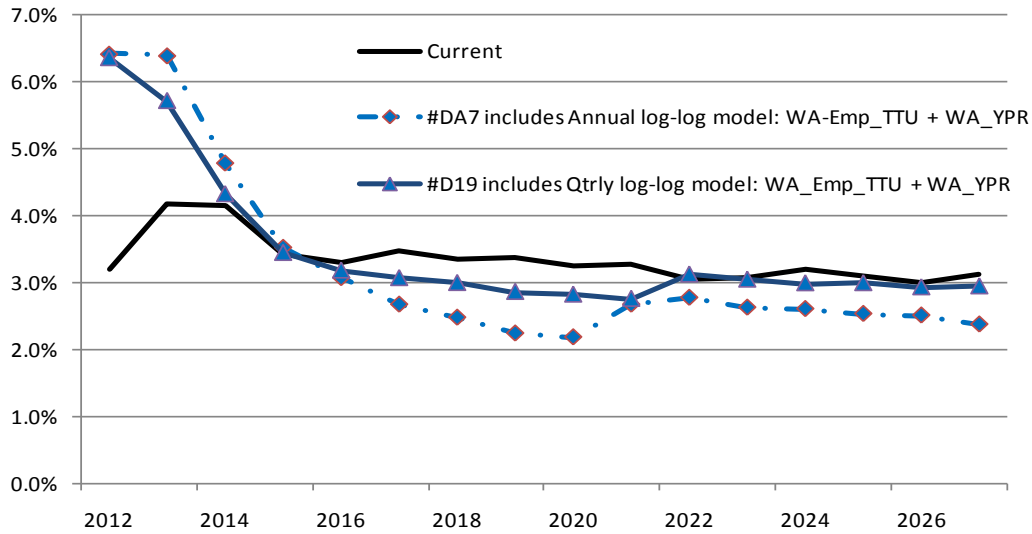
Model Parameters	Estimate	Std. Error	T-stat	Prob.
Intercept	-7.381	1.0357	-7.126	<0.0001
WA Employment_TTU (log)	0.9962	0.0423	2.353	0.0254
WA Personal Income (log)	0.611	0.267	2.288	0.0293
Adj. R ² =	0.981	RMSE =	22.95	
Schwarz Bayesian Criterion	237.11			

The best alternative annual and quarterly diesel consumption models growth rates are compared with the current law September 2010 forecast in Figure 25. In the near-term the alternative diesel consumption model has higher growth rates, a little more than 6% annually for both models, compared to the current forecast growth rate of a little more than 3%. In fiscal year 2013, the difference between the alternative model growth rates and the baseline growth rates declines slightly as the alternative diesel consumption models' growth rate fall to a little less than 6% and the current law forecast growth rates increase to a

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little more than 4%. By fiscal year 2014, the alternative model growth rates are nearly the same as the current law annual growth rate. In fiscal years 2015 and beyond, the alternative annual diesel model growth rates are always slightly below the current law forecast growth rates.

FIGURE 25. BEST ANNUAL AND QUARTERLY ALTERNATIVE DIESEL CONSUMPTION MODEL GROWTH RATES



Chapter 3: New Gasoline and Diesel Consumption Forecast Models

The forecast workgroup reviewed various combinations of independent variables and functional forms to arrive at the best alternative quarterly and annual gas and diesel consumption forecast models. The review examined data issues, model specifications, critical assumptions, and forecast performance. In arriving at the best alternative models, the workgroup examined the correlation between independent variables closely to verify that severe multicollinearity did not exist between independent variables in the regression model. The workgroup's review of the statewide fuel forecasts arrived at the following new econometric fuel consumption forecast models' specification and as outlined below.

FINAL QUARTERLY AND ANNUAL GASOLINE FORECASTING MODELS

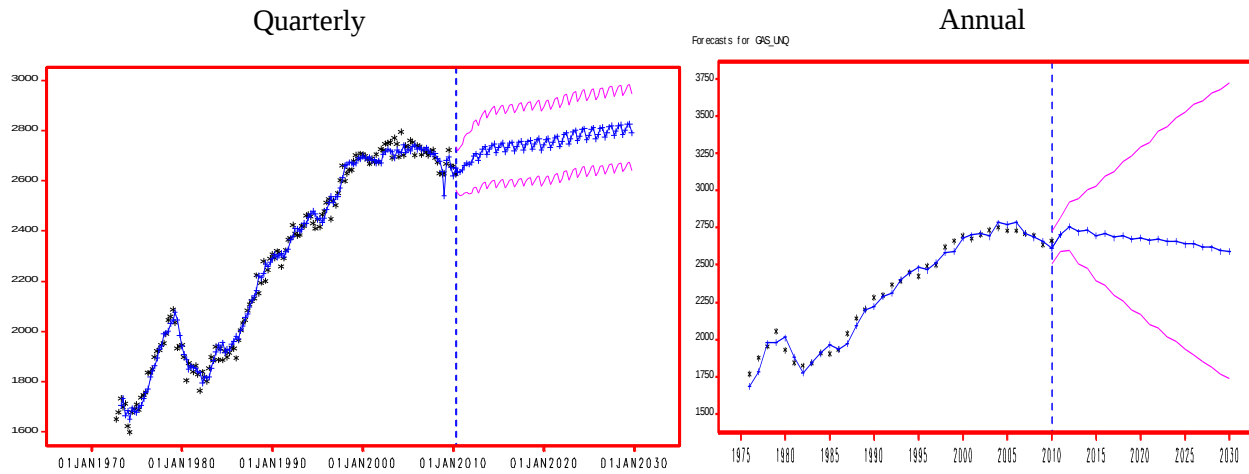
Gas Consumption Models

The technical workgroup determined that the best econometric quarterly gas consumption forecast model that had more than one independent variable would be preferred. The new quarterly forecast model has an economic activity variable, Washington non-farm employment, a composite variable of Washington retail gas prices multiplied by US average fuel efficiency, and a dummy variable for periods of oil shortages to be the independent variables. The economic activity variable, Washington non-farm employment, was chosen because it helps captured those periods of recessions when there may be less passenger vehicles and business traffic driving on the roads and less fuel being consumed. As more people become employed, fuel consumption should increase some as well. Washington gas prices and US fuel efficiency are multiplied together to create a composite variable which represents the negative forces which can reduce gas consumption. The gas price variable explains that in certain period of rising gasoline prices, people may drive less and gas consumption can fall. In the future, fuel efficiency is expected to rise substantially which will reduce people's demand for fuel and consumption will be negatively impacted. The addition of Washington gasoline prices and fuel efficiency add a different driver to the quarterly forecast model because it explains a different trend not yet captured by the economic variable.

The best alternative annual gas consumption model includes the same independent variables used in the quarterly model (Washington non-farm employment and composite variable) and adds Washington population. Adding Washington population produced slightly better statistics than not including it in the annual forecast model. Also having Washington population in the long-term should help the model reflect the impact of changing population on the state's consumption of fuel.

The final quarterly and annual models are log-log functional models solved using ordinary least squares. The annual gas consumption forecast model is also a first difference model which reflects the change in the independent variables from the previous year, not just the actual value of the variables.

FIGURE 26. HISTORICAL QUARTERLY AND ANNUAL FUEL CONSUMPTION AND BEST ALTERNATIVE FORECAST MODEL ESTIMATES



* denote actual gallons

+ denote forecast model estimate

Solid pink lines denote 95% confidence interval

MODEL EVALUATION

The new gasoline consumption forecast methodology and model was accepted by the technical workgroup. The estimated model statistics (i.e. coefficients, t-statistics, R-squared, White noise tests, unit root tests) were examined for both the quarterly and annual models. The individual regression coefficients are significant and have reasonable values. The model fits the historical gasoline consumption data well. Overall, the independent variables are able to explain most of the variation in gasoline consumption.

Forecasting Methodology and Model

Quarterly Model

- Equation – The equation for gasoline consumption in Washington is defined as

$$\ln(\text{Gas}) = \alpha + \phi \ln(\text{WA_Emp}) + \varphi(\text{WA_GasP*Eff}) + \delta(\text{Dummy}) + \varepsilon$$

Where

Gas = Quarterly gross gas consumption from Treasurer Reports (log),

WA_Emp = Quarterly Washington non-farm employment (log),

WA_GasP*Eff = Quarterly Washington gas prices * US average fuel efficiency (log) lagged 2 quarters,

Dummy = Quarterly dummy variable for periods of severe oil shortages.

And

ε = Stochastic disturbance on gasoline consumption.

The model also has first and second-order autoregressive terms to correct for serial correlation. The model has an Adjusted R-squared value of 0.99 and a root mean square error of 35.45. The t-statistics for the variables include 15.91 for the Washington employment, -5.16 for the lagged composite variable of Washington gas prices and fuel efficiency. The model statistics are presented in the following table.

FIGURE 27. WASHINGTON QUARTERLY GASOLINE CONSUMPTION FORECAST MODEL STATISTICS

Dependent Variable: LOG(GAS)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	2.38	0.311	7.668	<0.0001
LOG_WA Emp	0.737	0.046	15.91	<0.0001
LOG_US Fuel Efficiency * WA_GasP (lag 2 qtrs)	-0.091	0.018	-5.16	<0.0001
Dummy (period of oil shortages)	-0.026	0.012	-2.23	0.0273
AR(1)	0.543	0.080	6.829	<0.0001
AR(2)	0.300	0.080	3.743	0.0003
Adjusted R-squared	0.99			
Root Mean Square Error	35.45	Schwarz Bayesian criterion	1093.3	

Source: Regression run based on June 2010 economic variables forecast

- Forecast drivers – Washington employment has the strongest explanatory power in the forecast model of the two independent variables. It is positively correlated to gas consumption. The model's coefficient value for the Washington employment is 0.74, which in a log model is also the employment elasticity for gas consumption. Gas prices times US fuel efficiency is not as important in the forecast model but it is negatively correlated with gas consumption and is statistically significant.

FIGURE 28. QUARTERLY GAS CONSUMPTION FORECAST MODEL: AUTOCORRELATIONS

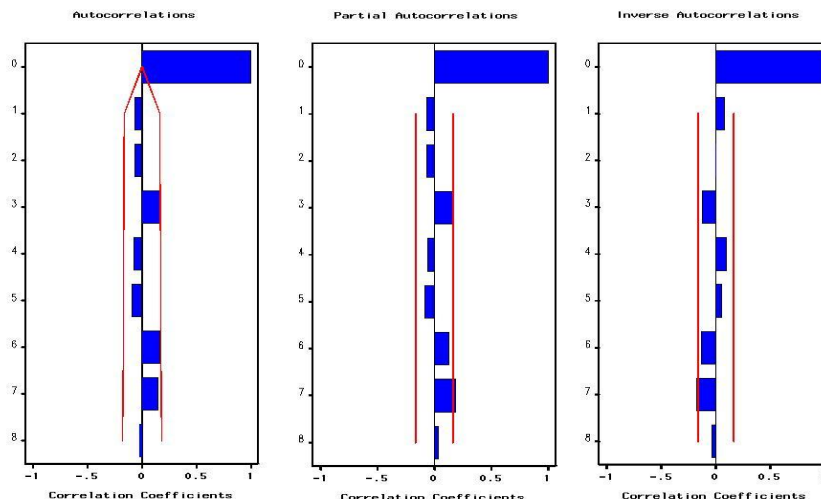
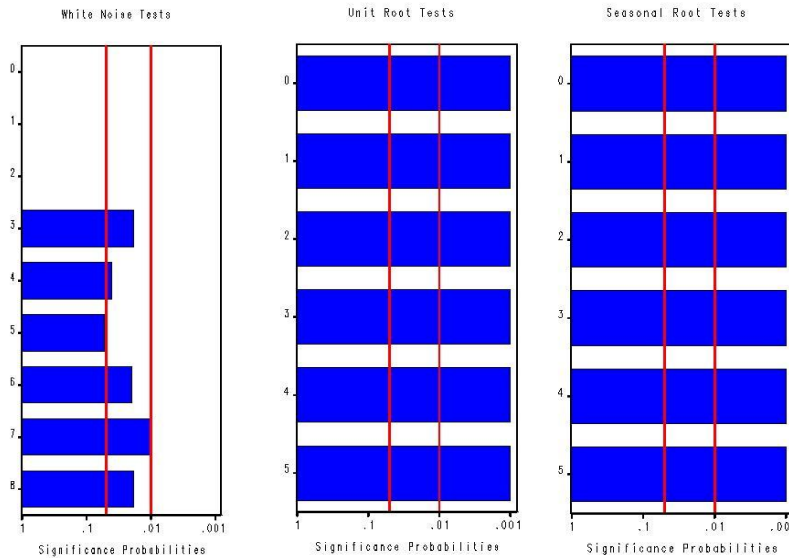


FIGURE 29. QUARTERLY GAS CONSUMPTION FORECAST MODEL: WHITE NOISE AND UNIT ROOT TESTS



Annual Model

- Equation – The equation for gasoline consumption in Washington is defined as

$$\ln(\text{Gas}) = \alpha + \phi \ln(\text{WA_Emp}) + \varphi(\text{WA_GasP*Eff}) + \delta \ln(\text{WA_pop}) + \varepsilon$$

Where

Gas = annual gross gas consumption from Treasurer Reports (log),
 WA_Emp = annual Washington non-farm employment (log first difference),
 WA_GasP*Eff = annual Washington gas prices * US average fuel efficiency (log),
 WA_pop = annual Washington population (log first difference)

And

ε = Stochastic disturbance on gasoline consumption.

The model also has first and second-order autoregressive terms and a moving average term of lag two to correct for serial correlation.

The log-log model has an Adjusted R-squared value of 0.979 and a root mean square error of 45.38. The t-statistics for the variables include 2.31 for the change in Washington employment, 2.99 for the change in Washington population and -2.54 for the Washington gas prices. The model statistics are presented in the following table.

FIGURE 30. WASHINGTON ANNUAL GAS CONSUMPTION FORECAST MODEL STATISTICS

Dependent Variable: LOG(VMT)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	7.788	0.385	20.22	<0.0001
LOG & 1 st Diff (WA_Emp)	0.442	0.191	2.31	0.0282
LOG & 1 st Diff (WA_Pop)	2.634	0.882	2.99	0.0058
LOG(WA_GasP*Efficiency)	-0.065	0.026	-2.54	0.0170
MA(2)	0.545	0.229	2.38	0.0242
AR(1)	0.978	0.059	16.48	<0.0001
AR(2)	0.913	0.146	6.26	<0.0001
Adjusted R-squared	0.979			
Root Mean Square Error	45.38	Schwarz Bayesian criterion	291.9	

Source: Regression run based on June 2010 economic variables forecast

- Forecast drivers – The change in Washington population has the strongest explanatory power in the forecast model of all three independent variables. It is positively correlated with fuel consumption. The model's coefficient value for the change in Washington employment is 0.44, which in a log model is also the employment elasticity for gas consumption. The change in Washington population has an even stronger positive correlation to gas consumption as the coefficient is 2.63. The composite variable of gas prices times fuel efficiency is not as important in the forecast model as the other two drivers as the coefficient is -0.065 but it is still negatively correlated with gas consumption and statistically significant.

FIGURE 31. ANNUAL GAS CONSUMPTION FORECAST MODEL: AUTOCORRELATIONS

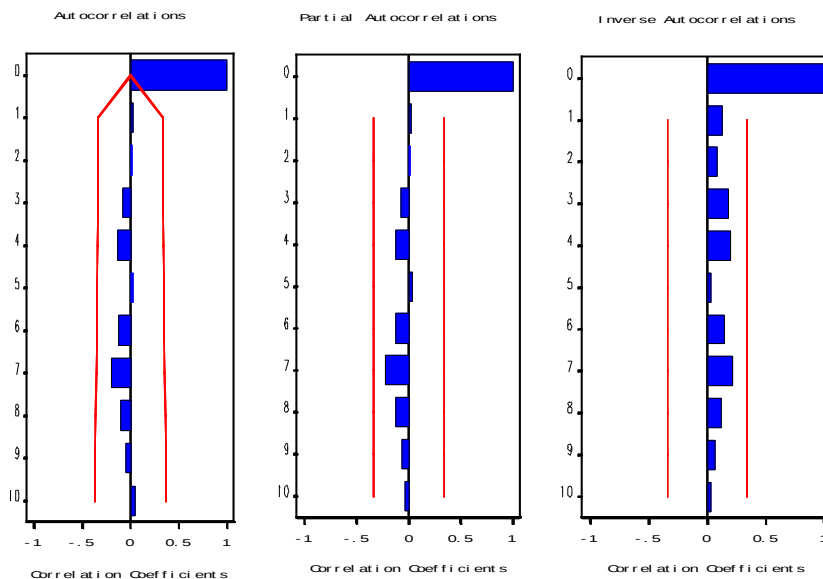


FIGURE 32. ANNUAL GAS CONSUMPTION FORECAST MODEL: WHITE NOISE AND UNIT ROOT TESTS

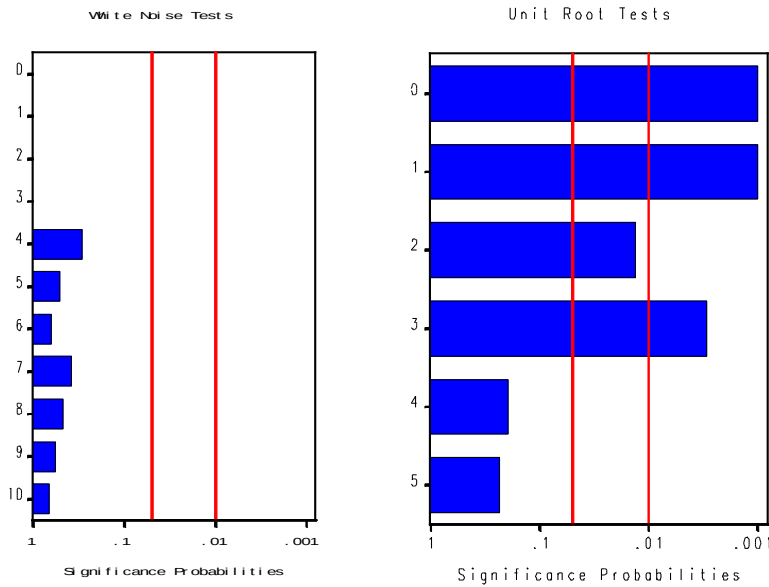


FIGURE 33. TOP GAS CONSUMPTION QUARTERLY & ANNUAL FORECAST MODELS CONSIDERED

Model description	RMSE	Adj. R squared	Schwarz Bayesian Criterion
Qtr: Log WaEmp + Log GasP*Fuel Eff	35.45	0.99	1093
Qtr: Log WaPop + Log GasP*Fuel Eff	36.82	0.99	1105
Qtr: Log WaPersonalIncome + Log GasP*Fuel Eff	38.12	0.99	1115
Annual: Log WaEmp + Log GasP*Fuel Eff + WAPop	45.38	0.98	292
Annual: Log WaEmp + Log GasP*Fuel Eff	46.01	0.98	289
Annual: Log WaEmp + Log GasP*Fuel Eff + WAPersIncome	46.15	0.98	293

The yellow highlighted model represents the final quarterly and annual gas consumption forecast regression models

Other Multivariate Forecast Model Specifications Considered

- For the quarterly gas consumption forecast, another top gas consumption forecast model considered included Washington personal income plus the composite variable of gas prices and fuel efficiency. This model was not selected because Washington personal income did not historically track with the actual gas consumption as well as Washington non-farm employment. In addition, since personal income is broad in nature, an increase in personal income may not translate into increased fuel consumption.

Chapter 3: New Gasoline and Diesel Consumption Forecast Models

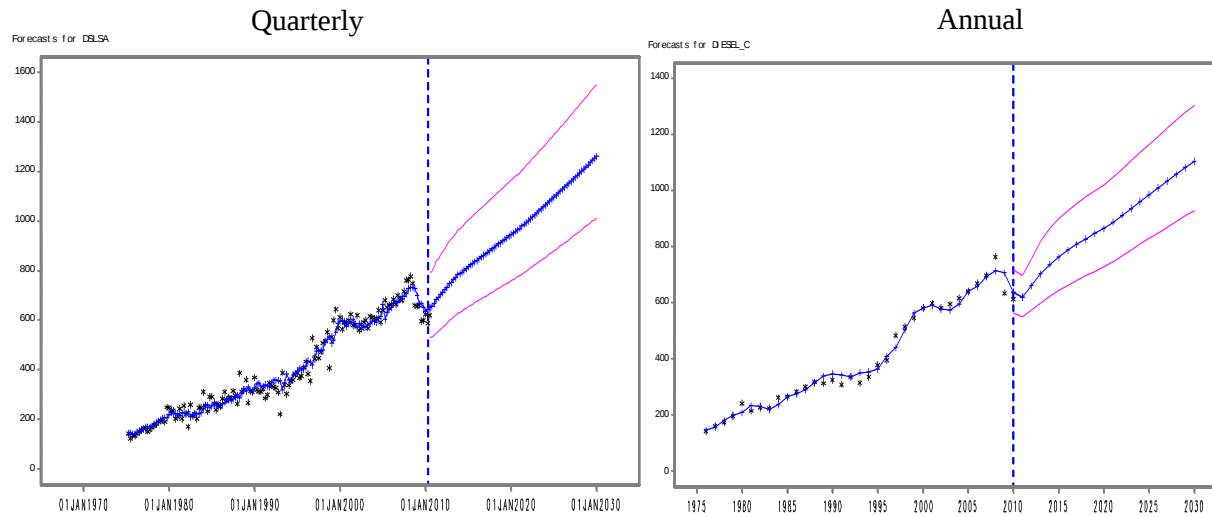
- Another top quarterly gas consumption forecast model considered was combining population with the composite variable of gas prices and fuel efficiency. This model was not selected because the employment variable did a better job at explaining past gas consumption than population did.
- Another best annual gas consumption model specification option considered was Washington employment with just the composite variable of gas prices and fuel efficiency. This option is very similar to the final best annual model in that it does not include Washington population when the final best annual gas model does. Having population in the regression model may be beneficial for future predictions. One drawback to this model is that it lacks the long term trends in population which the best annual gas consumption model provides.
- Another best annual gas consumption model specification option considered was Washington employment, the composite variable of gas prices and fuel efficiency and Washington personal income. This option is similar to the final best annual model except it uses Washington personal income instead of population. One drawback to this model was that Washington personal income was a broad measure that will increase for numerous reasons but may not result in additional driving and gas consumption.
- During the course of the forecast review, model results were also run on truncated quarterly gas consumption data beginning in fiscal year 2000. Some workgroup members asked for a truncated model because the trend in gas consumption in recent years has been flatter than the longer history. The truncated model produced very similar forecasts of gas consumption. Because of this, the work group agreed to retain the longer term quarterly history of gas consumption.

FINAL QUARTERLY AND ANNUAL DIESEL FORECASTING MODELS

Diesel Consumption Models

The technical workgroup determined that the best econometric quarterly diesel consumption forecast model had two independent variables. The new quarterly forecast model has an economic activity variable, Washington employment in the trade, transportation, and utilities sectors and Washington real personal income as the independent variables. The economic activity variable, Washington employment in the trade, transportation, and utilities sectors, was chosen because it helps capture those periods of recessions when there may be less production or commercial trucking demand and less fuel is consumed. As business and production picks up, demand for goods and trucking should increase some as well. Washington real personal income was included in the model to capture the state's business cycles as a proxy for diesel demand. The best alternative annual diesel consumption model includes the same two independent variables as the quarterly model. The final quarterly and annual models are log-log functional models solved using ordinary least squares.

FIGURE 34. HISTORICAL QUARTERLY AND ANNUAL DIESEL CONSUMPTION AND BEST ALTERNATIVE FORECAST MODEL ESTIMATES



* denote actual gallons

+ denote forecast model estimate

Solid pink lines denote 95% confidence interval

MODEL EVALUATION

The new diesel consumption forecast methodology and model was accepted by the technical workgroup. The estimated model statistics (i.e. coefficients, t-statistics, R-squared, White noise tests, unit root tests) were examined for both the quarterly and annual models. The individual regression coefficients are significant and have expected signs. Overall, the independent variables are able to explain most of the variation in diesel consumption. The model fits the historical diesel consumption data well.

Forecasting Methodology and Model

Quarterly Model

- Equation – The equation for diesel consumption in Washington is defined as

$$\ln(\text{Diesel}) = \alpha + \phi \ln(\text{WA_Emp_TTU}) + \varphi(\text{WA_PersInc}) + \varepsilon$$

Where

Diesel = Quarterly gross diesel consumption from Treasurer Reports (log),

WA_Emp_TTU = Quarterly Washington employment in trade, transportation & utilities sectors (log),

WA_PersInc = Quarterly Washington real personal income (log).

And

ε = Stochastic disturbance on diesel consumption.

Chapter 3: New Gasoline and Diesel Consumption Forecast Models

The model also has first and second-order autoregressive terms to correct for serial correlation. The model has an Adjusted R-squared value of 0.96 and a root mean square error of 36.55. The t-statistics for the variables include 2.36 for the Washington employment_TTU, 5.54 for Washington real personal income. The model statistics are presented in the following table.

FIGURE 35. WASHINGTON QUARTERLY DIESEL CONSUMPTION FORECAST MODEL STATISTICS

Dependent Variable: LOG(Diesel)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-7.88	0.516	-15.25	<0.0001
LOG(WA_Emp_TTU)	0.596	0.253	2.36	0.0197
LOG(WA_PersInc)	0.855	0.155	5.54	<0.0001
AR(1)	0.228	0.084	2.72	0.0074
AR(2)	0.194	0.085	2.29	0.0232
Adjusted R-squared	0.96			
Root Mean Square Error	36.55	Schwarz Bayesian criterion	1046.8	

Source: Regression run based on September 2010 economic variables forecast

- Forecast drivers – Washington real personal income has the strongest explanatory power in the forecast model. It is positively correlation to diesel consumption. The model's coefficient value for the Washington real personal income is 0.855 which in a log-log model is also the income elasticity for diesel consumption. Washington employment in the trade, transportation and utilities sector diesel coefficient value is 0.596 which in the log-log model is the employment elasticity for diesel consumption.

FIGURE 36. QUARTERLY DIESEL CONSUMPTION FORECAST MODEL: AUTOCORRELATIONS

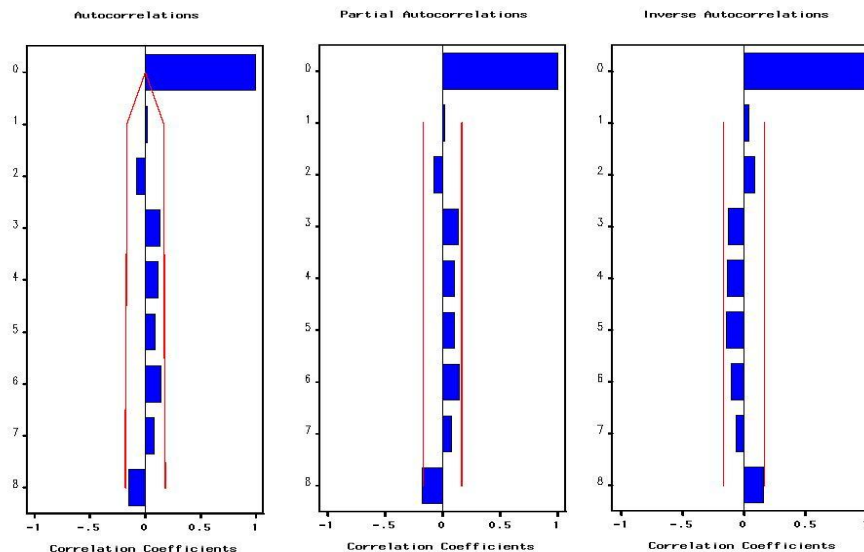
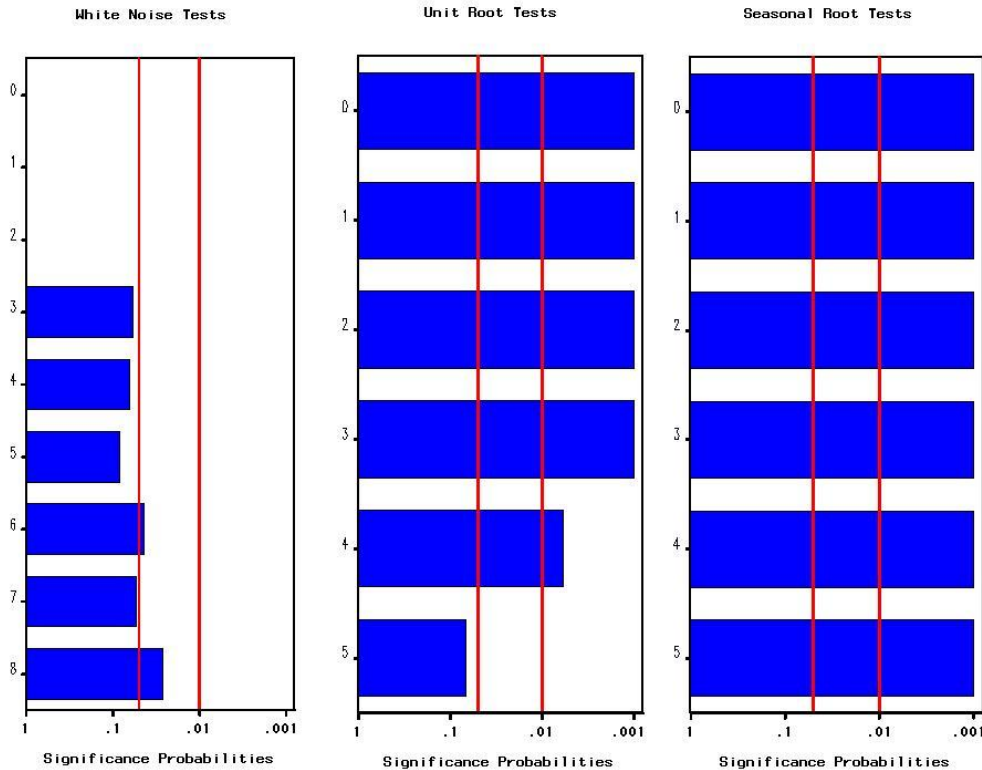


FIGURE 37. QUARTERLY DIESEL CONSUMPTION FORECAST MODEL: WHITE NOISE AND UNIT ROOT TESTS



Annual Model

- Equation – The equation for diesel consumption in Washington is defined as

$$\ln(\text{Diesel}) = \alpha + \phi \ln(\text{WA_Emp_TTU}) + \varphi(\text{WA_PersInc}) + \varepsilon$$

Where

Diesel = annual gross diesel consumption from Treasurer Reports (log),
 WA_Emp_TTU = annual Washington employment in trade, transportation & utilities sectors (log),
 WA_PersInc = annual Washington real personal income (log).

And

ε = Stochastic disturbance on diesel consumption.

The model also has first and second-order autoregressive terms to correct for serial correlation.

The log-log model has an Adjusted R-squared value of 0.981 and a root mean square error of 22.95. The t-statistics for the variables include 2.35 for Washington employment_TTU and 2.29 for the Washington real personal income. The model statistics are presented in the following table.

FIGURE 38. WASHINGTON ANNUAL DIESEL CONSUMPTION FORECAST MODEL STATISTICS

Dependent Variable: LOG(Diesel)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-7.381	1.036	-7.126	<0.0001
LOG (WA_Emp_TTU)	0.996	0.042	2.35	0.0254
LOG (WA_PersInc)	0.611	0.267	2.29	0.0293
AR(1)	0.571	0.171	3.35	0.0022
AR(2)	0.304	0.208	1.46	0.1536
Adjusted R-squared	0.981			
Root Mean Square Error	22.95	Schwarz Bayesian criterion	237.1	

Source: Regression run based on September 2010 economic variables forecast

- Forecast drivers – The Washington employment in the trade, transportation and utilities sectors variable has the strongest explanatory power in the forecast model. It is positively correlated to diesel consumption. The model's coefficient value for Washington employment in the trade, transportation and utilities sectors is 0.996 which in a log model is also the employment elasticity for diesel consumption. Washington real personal income has a strong positive correlation to diesel consumption as the coefficient is 0.61.

FIGURE 39. ANNUAL DIESEL CONSUMPTION FORECAST MODEL: AUTOCORRELATIONS

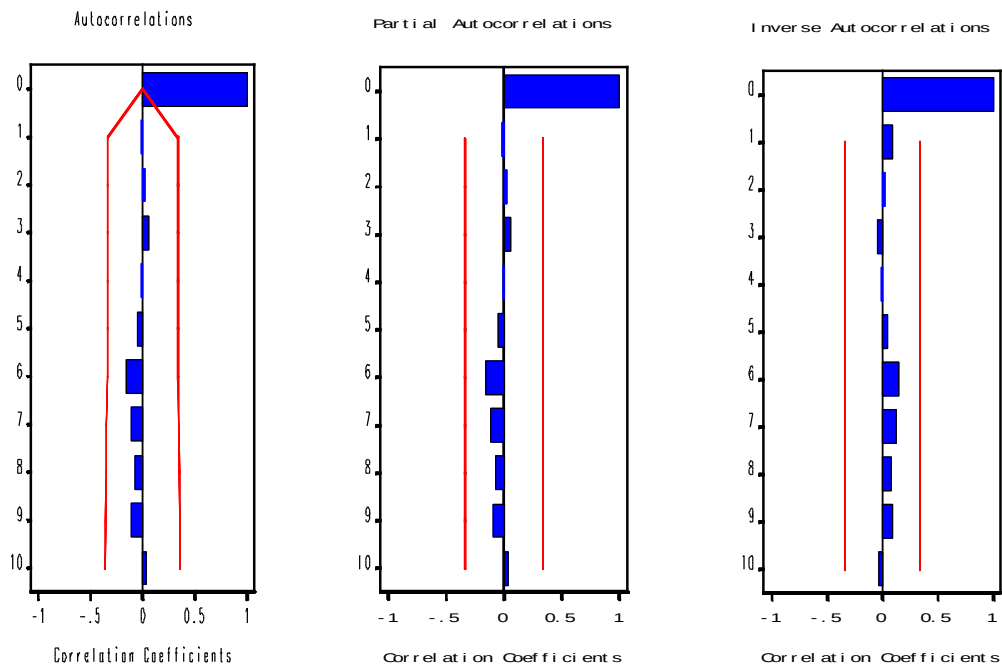


FIGURE 40. ANNUAL DIESEL CONSUMPTION FORECAST MODEL: WHITE NOISE AND UNIT ROOT TESTS

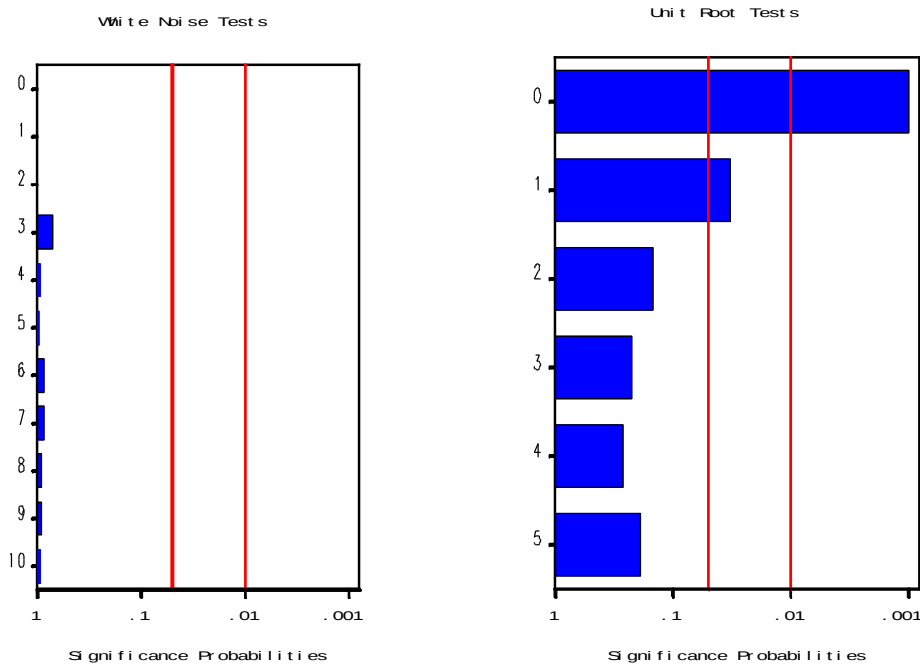


FIGURE 41. TOP DIESEL CONSUMPTION QUARTERLY & ANNUAL FORECAST MODELS CONSIDERED

Model description	RMSE	Adj. R squared	Schwarz Bayesian Criterion
Qtr: Log WaEmp_TTU + Log WAPersonalIncome	36.55	0.96	1046.8
Qtr: Log WaEmp_TTU + US Exports	37.77	0.96	1056.1
Annual: Log WaEmp_TTU + Log WAPersonalIncome	22.95	0.98	237.1
Annual: Log WaEmp_TTU + US Exports/Imports	20.89	0.99	230.6

The yellow highlighted model represents the final quarterly and annual diesel consumption forecast regression models

Other Multivariate Forecast Model Specifications Considered

- Another top quarterly diesel consumption forecast model considered was Washington employment in trade, transportation and utilities sectors with US exports. This model was not selected because it had excessive reliance on the trade sector as it has both the value of US exports and WA employment in the trade sectors as independent variables. Washington personal income has closer nexus with Washington state than US exports.
- Another annual model option considered was Washington employment_TTU with US exports and imports. This option is similar to the final best annual model but it included

the trade sector in both Washington employment in the trade transportation and utilities sectors and the value of the US exports and imports. One drawback to this model is that it can depend too much on the trade sector. One advantage of the final annual diesel consumption model is that it has close nexus to Washington state with Washington real personal income in the model.

Other Statistical Tests

- Autocorrelations
 - Autocorrelation function plots show the degree of correlation with past values of a series as a function of the number of periods in the past (that is, the lag) at which the correlation is computed.
 - Figures 28, 31, 36 and 39 reveal in the current period (lag 0), all three of the autocorrelations have high correlation (nearly 1) which is a sign of a strong relationship between the dependent and independent variables in the model
 - By examining the plots in Figures 28, 31, 36 and 39, one can judge whether the series is stationary or nonstationary. In this case, a visual inspection of the autocorrelation function plot indicates that the fuel consumption series is stationary, since the autocorrelation function decays quickly. In subsequent periods, the autocorrelations decrease significantly and stay within the red lines depicting the confidence band.
 - The sample inverse autocorrelation function (SIACF) can be useful for detecting over-differencing. If the data come from a nonstationary or nearly nonstationary model, the SIACF has the characteristics of a noninvertible moving-average. Likewise, if the data come from a model with a noninvertible moving average, then the SIACF has nonstationary characteristics and therefore decays slowly. In this case, the SIACF decays quickly revealing a stationary series.
 - All three autocorrelation graphs reflect a stationary series
- White Noise Tests
 - Tests were performed for model “white noise” or randomness implying that the sum of the squares of a group of consecutive autocorrelations should all sum to 0 for all periods
 - Ljung-Box Chi-square statistic – joint test for autocorrelations of residuals; this considers several autocorrelations together to calculate a statistic that has chi-square distribution
 - Figures 29, 32, 37 and 40 “White noise” tests reveal the significance possibilities of the Ljung-Box Chi-square statistics for 16 periods
 - Each bar shows the probability computed on autocorrelations up to the given lag with longer bars favoring rejection of the Null hypothesis that the prediction errors represent “White Noise” or randomness
 - In this case, the graphs in Figures 29, 32, 37 and 40 reveal a low level of significance meaning we can assume randomness in this gas consumption model

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- Unit Root Tests
 - Tests were performed to see if the time series was stationary and if unit roots appeared; if a series has a unit root, the series is nonstationary and then the ordinary least squares estimator is not normally distributed
 - The Augmented Dickey-Fuller single mean test was completed to test the hypothesis that the variables in the model have a unit root
 - Figures 29, 32, 37 and 40 unit root tests reveal the results of the unit root tests by showing the significant probabilities of the Augmented Dickey-Fuller test for unit roots;
 - When the horizontal bars on the graph are longer and beyond the first vertical line, then you can reject the Null hypothesis that the series is non-stationary, meaning the series is stationary.
 - The model results indicate that the series is stationary because the significance probability is above the threshold for the current and prior two periods.

Source of Independent Forecasted Variables

- Washington employment – The forecast for Washington employment was taken from the Economic and Revenue Forecast Council June 2010 forecast in the near-term and from OFM/ESD's 2009 long-term non-farm employment projections for Washington.
- Washington population – The forecast for Washington population was based on OFM's 2009 long-term population forecast
- US Fuel efficiency – The forecast for US fuel efficiency was based on June 2010 IHS Global Insight forecast
- Washington gasoline prices – The forecast for Washington retail gasoline prices was taken from the WSDOT forecast for the Transportation Revenue Council for June 2010 forecast

Critical Forecast Assumptions

- Forecast Procedure – The calculation of the new fuel consumption forecasts each year will consist of running the econometric forecast model with new fuel consumption actual and economic variables. The new forecast will be based on the quarterly regression model growth rates through FY 2013 and then the long term growth rates will be used for the remainder of the forecast horizon. This procedure helps reset the new forecast to the last known actual gasoline consumption while applying the same model growth rates.

Chapter 4: Forecast Impacts and Conclusions

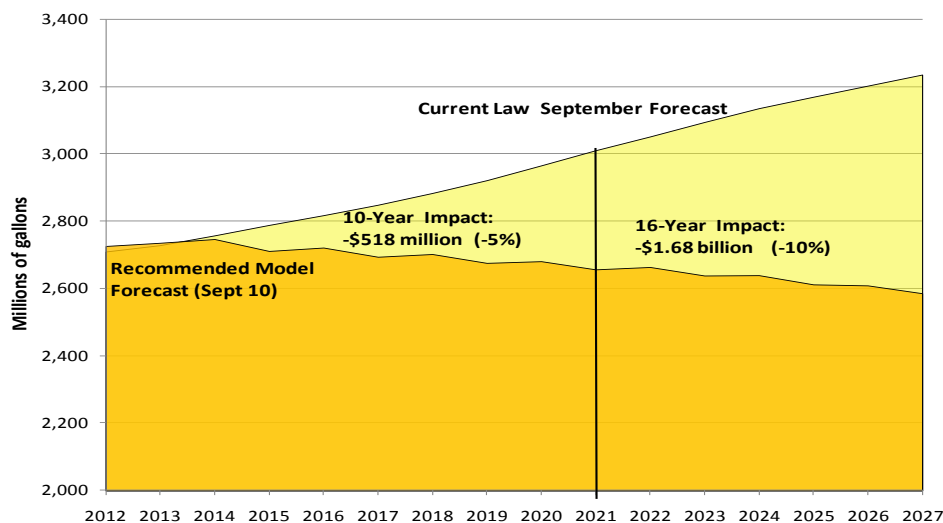
Fuel consumption, in particular gasoline consumption, has flattened in recent years and the revised gasoline consumption forecast model has reflected a slower growth for future gasoline consumption. In contrast, diesel consumption has declined significantly in the recent recession but the old diesel model underestimated actual diesel consumption from 2000-2008. The revised diesel consumption forecast model produces slightly higher diesel consumption forecasts than the current law forecast in September 2010. This overall change in the total motor fuel consumption forecast will result in lower total motor fuel consumption projections. In the past, the gasoline consumption forecast model had been reasonably accurate but in recent years had become progressively less accurate. The actual gas consumption by 2010 had been more than two standard deviations below the average forecast. The diesel consumption model also had been producing forecasts that were above the actual diesel consumption in 2009 and 2010 which had been the first time that this diesel consumption model had overestimated actual consumption and performed that poorly.

Forecast Impacts

Gasoline Tax Revenue

The work group compared the new gasoline consumption forecast model with the September 2010 economic variables. The September 2010 gas tax revenue projections from the new model would increase revenue slightly in the near-term and fall significantly in the long-term. The ten year revenue impact from implementing the new gas model is a reduction of \$518 million, or 5% of current projections. The sixteen year revenue impact is a reduction of \$1.68 billion, or 10% of total revenues.

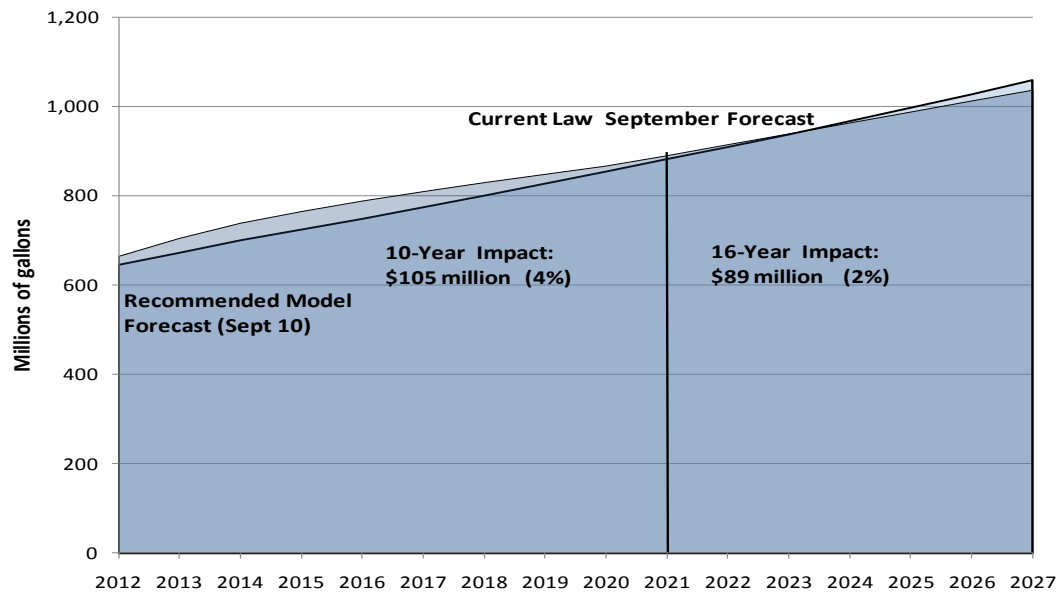
FIGURE 42. BEST QTRLY & ANNUAL WA GAS CONSUMPTION MODELS COMPARED TO SEPTEMBER 2010 FORECAST: 10 AND 16 YEAR REVENUE IMPACT ESTIMATES



Diesel Tax Revenue

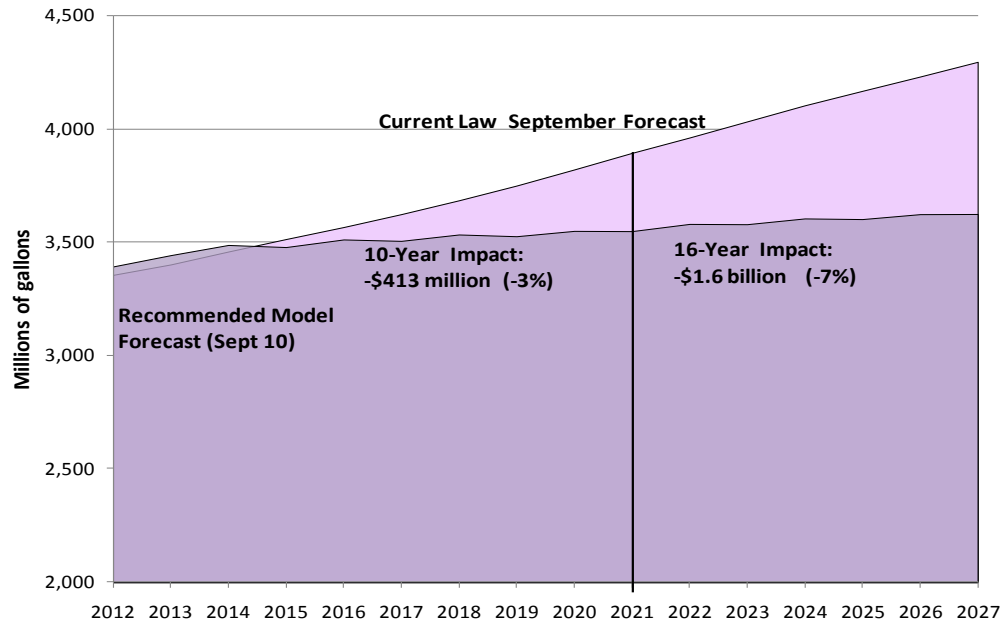
The new diesel consumption forecast model was used with the September 2010 economic variables. The results from this analysis are in Figure 43. It reveals that the new model would increase diesel tax revenues throughout most of the forecast horizon. By FY 2022, revenue of the new model projections would be nearly the same as the September 2010 current forecast and slightly lower forecasts in FY 2025 and beyond. The ten year revenue impact from implementing the new diesel model is an increase overall of \$105 million or 4% of current projections. The sixteen year revenue impact is an increase of \$89 million or 2% of total diesel tax revenues.

FIGURE 43. BEST QTRLY & ANNUAL WA DIESEL CONSUMPTION MODELS COMPARED TO SEPTEMBER 2010 FORECAST: 10 AND 16 YEAR REVENUE IMPACT ESTIMATES



Combining the impact of both new fuel consumption forecast models with the September economic variables results in following impacts compared to the baseline September 2010 forecast as reported in Figure 44. The ten year impact is a reduction in tax revenue of \$413 million or 3% of the total revenues estimated in the September 2010 baseline forecast. The sixteen year impact is a reduction in tax revenue of \$1.6 billion or 7% of total estimated revenues from the September forecast.

FIGURE 44. BEST QTRLY & ANNUAL WA GAS AND DIESEL CONSUMPTION MODELS COMPARED TO SEPTEMBER 2010 FORECAST: 10 AND 16 YEAR REVENUE IMPACT ESTIMATES



Recommendations for further research includes the following:

The Technical Workgroup should review these forecast models again in a few years to see if truncating the data would produce better forecasts than using the longer term history of gas consumption. Periodically the group should monitor and coordinate consistency between the various transportation related forecasts.

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Appendix I: State Survey of Fuel Consumption Models

The following table provides a summary of states contacted in 2010 about their current fuel consumption forecast model. The seventeen states below reflect ones that the work group requested WSDOT to contact. Some states were surveyed previously during the 2006 transportation revenue forecast review.

State	Type of model	Gas Model Details	Diesel Model Details
Arizona	econometric	Log model with fuel efficiency, real per capita personal income, pop growth rates, wage and salary growth rates. Does not include a price variable	
California	econometric	New model in development	
Colorado	econometric	New model in development	
Connecticut	econometric	no model but examine recent tax collections and examine recent fuel prices; use rolling average of recent collections to forecast; forecast out 2-5yrs	
Florida	econometric	real price of fuel, real personal income, fleet miles per gallon, and total households	
Idaho	econometric	ID non-farm employment, fuel efficiency, avg. national nominal gas prices & dummy variable for change in location for fuel tax collection	
Indiana	econometric	First: Regression models forecast the number of registrations in each category of motor vehicles; Second: fleet fuel efficiency is determined by the age of the vehicle and by estimates on VMT by age; Third: fuel consumption is calculated by dividing VMT/Fleet Fuel Efficiency	
Missouri	econometric	log real gas prices, log fuel efficiency, log pop & dummy variable	
North Carolina	econometric	Combined gas and diesel consumption: reviews recent fuel consumption and population growth rates and examines fuel prices heavily as their fuel tax rate is variable based on wholesale price of fuel; also reviews Congressional Budget Office forecast of Highway Trust Fund	
New York	econometric	NY personal income and fuel prices	real Gross Domestic Product
Ohio	econometric	log- log model: fuel efficiency, employment, population, real OH gas prices	Gross State Product (OH), truck fuel economy, OH diesel prices

Oregon	econometric	combined diesel & gas model; non-farm employment; gas prices (3 qtr dist. lag); fuel efficiency; real personal income; change in MI-consumer sentiment	
Pennsylvania	econometric	No model	No model
Texas	econometric	population; sometimes fuel prices	gross state product
Vermont	econometric	fuel consumption per capita dependent variable: gross domestic product or real personal income + price variable + population	diesel consumption per capita (unit tax) dependent variable: gross domestic product or real personal income + price variable + population
West Virginia	econometric	Has both a flat fixed fuel tax as well as a variable rate tax; No formal forecasting models but examines Global Insight variables; WV looks to Global Insight for Producer Price Index-petroleum products for setting wholesale price of fuel & future national consumption data	
Wisconsin	econometric	log-linear regression model; real price of gasoline, fuel efficiency variable, real disposable income, vehicle fleet, dummy variable for oil shortages	