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Overview

The attached report, prepared by Energetics, Inc., under contract to Z, Inc, under contract to the U.S. Energy Information Administration (EIA), provides a review of literature related to short-term gasoline consumption forecasting.

Understanding the development and evolution of the domestic gasoline market is of great importance to EIA. EIA's Office of Energy Analysis (OEA) publishes the *Short-Term Energy Outlook* (STEO) monthly. STEO includes the official EIA forecast of domestic energy markets through the end of the next calendar year. To support this forecast, the primary analysis tool is the Regional Short-Term Energy Model (RSTEM), which OEA is responsible for developing and maintaining.

EIA is in the process of evaluating the inputs to the motor gasoline consumption module in RSTEM, as well as the modeling equation's structure. EIA's motor gasoline consumption model is based on two estimated regression equations, one for vehicle miles traveled and one for vehicle fuel efficiency (measured in miles per gallon). These models forecast these two variables separately, and the model divides the resulting forecast of vehicle miles traveled by the forecast of fuel efficiency to arrive at total gallons of gasoline consumed. The vehicle miles traveled equation is estimated using population, gasoline price, and employment as the main variables. The fuel efficiency equation is a simple trend forecast adjusted for the real price of gasoline.

As a part of this model evaluation effort, EIA would like to better understand the approaches and methodology of outside experts who are also forecasting gasoline consumption over the short- and medium-term (two to five years.)

The attached paper is being shared as a contribution to the literature and to the ongoing dialogue on an energy topic of great importance. The views expressed in this contractor report are those of the authors, and they do not necessarily reflect the views of EIA. EIA intends to pursue further work related to this important topic.

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Short-Term Domestic Gasoline Consumption Modeling Literature Review

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1 Introduction

Gasoline consumption forecasting (both short- and long-term) is primarily useful for evaluating policies, such as those aimed at reducing automobile use, road use, or greenhouse gas emissions, and estimating future gasoline tax revenue and highway investment needs. Due to its practical application to policymaking, there is an abundance of relevant academic, government, and industry literature reviewing a variety of modeling approaches.

EIA's Regional Short-Term Energy Model (RSTEM) is the underlying analysis framework used to inform the monthly Short-Term Energy Outlook (STEO). The gasoline consumption forecast published in STEO is generated from 12 equations (3 of which are regressions) that use variables from other STEO components or external sources. EIA is interested in exploring the existing literature on short- and medium-term gasoline consumption modeling (2-5 years) to evaluate the inputs and structure of STEO's gasoline consumption module.

The current paper reviews relevant literature to identify the key determinants of gasoline consumption used in modeling efforts as well as model structures, and provides a concise summary of key findings and best practices for consideration in future updates to EIA's STEO gasoline consumption module. This review was accomplished in three steps. First, a preliminary literature review was conducted to determine some of the key sources of information on the elasticities of gasoline consumption. Second, an EIA-sponsored gasoline consumption modeling workshop was planned with some of the experts identified in step one. The third stage (this report) completes a more comprehensive literature review that assimilates all the findings from the first two steps and expands the amount of relevant literature and information contained therein.

The final literature review identifies the most frequently cited publications and attempts to cover the breadth of relevant information. As these publications were analyzed, their references were mined for additional literature. The primary literature reviews identified include: Dahl (2012); Basso and Oum (2007); Wadud (2007); Goodwin, Dargay and Hanly (2004); Graham and Glaister (2002); Espey (1998); Sterner and Dahl (1992); Dahl and Sterner (1991); Blum, Foos and Gaudry (1988); and Dahl (1986).[1] Over 100 papers were reviewed for this study, with many more identified as containing relevant content that were not reviewed due to schedule constraints. These additional resources are included in the project bibliography transmitted separately. In general, there is limited literature specifically addressing *short-term* gasoline consumption modeling; the clear majority covers the intricacies and dependencies of *short-run*, *long-run*, and *intermediate-run* elasticities, whether of price, income, other socioeconomic, or demographic variables.

The breadth of information and methodology for econometric modeling is massive and this paper attempts to concisely review gasoline consumption modeling basics in parallel to a topical review of the literature. This report focuses on several key studies and models, but numerous additional sources are provided within the text and in the separate bibliography for further investigation.

Section 2 provides a general overview of and brief introduction to the modeling classification system used in this report. Section 3 briefly summarizes EIA's STEO Gasoline Consumption Module structure

[1] Some older literature on national-level transportation/energy demand models was compiled in an annotated bibliography by Richardson (1980).

and inputs for reference and comparison to the literature. Section 4 presents the work from the first two steps of this project (initial literature search and workshop), which were primarily focused on price and income elasticities of gasoline demand/consumption. The prior work is supplemented by some of the elasticity findings from this final literature review. Section 5 describes literature findings on the key determinants of gasoline consumption, common (and unique) modeling methodologies and structures, and data requirements for model inputs. The topic of data disaggregation has gained more traction recently, primarily due to the recognition that elasticities are highly heterogeneous in multiple dimensions. Literature on this topic was extensive enough to warrant a separate section from the rest of the organized discussion.

Each section of the reports cites many sources. Schedule constraints did not allow for a detailed review of every source. Therefore, the most prominent (highly cited) publications were given higher priority, while citations for the remainder are provided for further review.

Regarding terminology, the following sets of words are used interchangeably throughout this review:

- *Independent* and *explanatory* when used to describe a non-dependent variable
- *Fuel efficiency* and *vehicle efficiency*
- *Demand* and *consumption* when used to describe how gasoline is being modeled

The third set does not reflect the authors' opinion or the literature's explicit disagreement with EIA's terminology. Rather, *demand* and *consumption* are used interchangeably and equivalently throughout the literature and this report reflects that.

2 Approaches to Consumption Forecasting

2.1 General Overview

Recent approaches to gasoline consumption modeling can be broken down into two basic categories: qualitative and quantitative. A qualitative approach relies on expert opinion, intuition, and knowledge, while a quantitative approach uses standard econometric modeling methods (or other mathematical approaches) to project relationships between different variables. The clear majority of published government, industry, and academia work has been quantitative. Qualitative features have been incorporated into existing models more frequently since the turn of the century, and is discussed in Section 5.4.2 of this report. Quantitative models take two foundational forms: time-series (non-explanatory or extrapolation) analysis and regression (explanatory) analysis.

Time-series analyses use time series data to generate forecasts based on a combination of trends, seasonal patterns, level shifts, outliers, and random error for a single data series. These models extrapolate a historical trend rather than exploring and describing underlying theoretical (causal) relationships between the dependent and independent variables. The most popular time-series gasoline consumption modeling approach identified in the literature is the auto-regressive integrated moving average (ARIMA) model, which is basically a weighted average of past observations. Or more technically, the explanatory variables are simply lagged values of the dependent variable and lags of the forecast errors. ARIMAs and other time-series models are attractive because of the low data burden: they only require one data series, and the data series can be easily adapted (by changing weights) to new information as it becomes available. Time-series models provide accurate short-term forecasts assuming normal and stable conditions, using a minimum amount of information. Generally, though, researchers agree that ARIMA and other time-series modeling should only be used when there is not enough data or information to properly specify an accurate and reasonable econometric or regression model (Gillen 2000). More details on time-series analyses are found in Section 5.4.1.

Econometric regression analysis is a statistical technique for estimating the relationship/s between a dependent variable and multiple independent or explanatory variables (multivariate). This is considerably more powerful than time-series approaches due to the ability to incorporate causal features in the data, which provides the modeler with the ability to explore "what if" analyses for different scenarios – an especially useful feature for policymakers to identify the impact of policy changes (e.g., changes in fuel tax, addition of carbon tax) (Berkowitz, et al. 1990). Regressions are generally better for longer-term modeling because they can allow for change in underlying variables, as opposed to the time-series approach, which assumes no change in underlying structural relationships. However, these underlying variables must also be forecast and therefore contain error that propagates through to the estimation of the variable of interest.[2] Data and theoretical knowledge requirements are significant drawbacks to econometric regression analysis; the modeler must ensure that the input data is sufficiently accurate, and that the model is properly specified. The most significant independent variables must be included, while those that are collinear or non-significant must be left out. Additionally, regressions tend to contain a large amount of serial autocorrelation that must be addressed. The most common estimation techniques used are ordinary least squares (OLS) and general least squares (GLS), although this paper does not discuss this differentiation any further.

The literature review also found a few novel approaches to forecasting gasoline consumption. One of the more frequently mentioned varieties involved models based on artificial neural networks (ANN). ANN-based models are totally data-driven and are not informed by any theoretical or behavioral underpinning. More discussion on unique approaches is provided in Section 5.4.

2.2 Model Types

Setting aside the qualitative approach for later discussion (see Section 5.4.2), this report adopts the terminology of Basso & Oum (2007) as the simplest and most descriptive method for categorizing common quantitative regression modelling approaches identified in the literature review.[3] There are four basic classification criteria: approach – reduced form versus structure; time – static versus dynamic; data type; and functional form. Overall, the literature heavily leaned toward reduced form, dynamic models employing aggregated time series or panel data and a log-linear functional form.

2.2.1 Reduced Form vs. Structural

The **reduced form** approach directly estimates gasoline demand as a function of relevant determinants (e.g. price or income) and is the most common approach found in the literature, likely due to its less stringent data requirements. It is solved using static and/or dynamic models; cross-sectional, time-series, or panel data; and/or considering different functional forms as described in the following sections.

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[2] As stated in Cervero (1985), oftentimes these explanatory variables are more difficult to forecast than the actual dependent variable.

[3] Other categorization terminology is discussed in older studies, for instance (Dahl and Sterner 1991; Blum, Foos and Gaudry 1988; Dahl 1986).

The **structural** approach[4] offers much greater explanatory power by decomposing the elasticities into sources. Rather than directly regressing gasoline consumption on independent variables, multiple components of gasoline consumption (e.g., vehicle miles travelled (VMT), fuel efficiency, vehicle stock) are modeled interdependently (but separately) and inserted into the final equation. This approach is far more demanding with respect to data requirements and economic theory, especially for models that attempt to explain more variation.[5] Reduced form equations for underlying variables (e.g., VMT or fuel efficiency) can be used to inform a structural equation. Examples of structural models include: those that use aggregated data, such as Johansson and Schipper (1997), Gallini (1983), and EIA's STEO Gasoline Consumption module; and disaggregated data, such as Archibald and Gillingham (1980), Eltony (1993), and Puller and Greening (1999).

Selection of the approach generally depends on the model's goal. If understanding how price and income effect the dependent variable (to predict effects from potential taxes, policies, or other factors) is most important, then additional explanatory variables will likely add unnecessary complication due to higher data requirements. This is especially true if the additional variables have very little influence on gasoline consumption outside of the indirect effects of price and income changes. On the other hand, if the model is aiming for a more accurate explanation of gasoline consumption trends, then capturing additional variables (thereby capturing their influences that go beyond the overlap with price or income) could reduce bias. More simply, a structural model provides more explanatory power at the cost of efficiency, while a simpler reduced form model offers less explanatory power with higher efficiency.

2.2.2 Time: Static vs. Dynamic

Static models assume that any change in the dependent variable is due to simultaneous variation in the independent variables, i.e. that there isn't any *lag* in response. This assumption is highly contested, since individual behavioral responses to changes in costs are not instantaneous, but rather take place over time. A similar problem attributed to static models suggests that the lack of time response simulates a future state of equilibrium response, which would only be reached if the input dataset values were held constant for some period of time. These issues have generally been thought to lead to intermediate-run, not clearly short- or long-run, elasticities. (See Brons, et al. (2008) for a meta-analysis confirming this). Multiple studies (Goodwin, Dargay and Hanly 2004; Schipper, et al. 1993; Dahl and Sterner 1991) find that static models deliver price elasticities between 31-33% smaller than those from dynamic models. The results for income elasticity are not as clear. It "is now standard in the fuel consumption literature" (Goodwin, Dargay and Hanly 2004) to use dynamic model specification so that the distinction between short- and long-run elasticities is clear.[6]

Dynamic or flow adjustment models account for the fact that consumer responses to economic changes take time. The most popular dynamic model identified by the literature is the lagged endogenous

[4] Also called an "indirect" or "components" model
[5] This is especially evident for cross-sectional data, for example, Baltagi and Griffin (1983) could not develop their theoretical structural model because of the lack of international data on miles driven and consumption per mile.
[6] This is the stance taken by most literature, although Basso and Oum (2007) and Dahl (2012) indicate that using co-integration techniques on a static model could re-validate the usefulness of static models (see Section 5.3.2 of this paper).

model,[7] which adds a lagged gasoline demand variable to the existing set of explanatory variables.[8] Lagged exogenous models, which use explicitly lagged values of selected independent variables, are far less common because of the multicollinearity that arises among the lagged variables. The dominance of the lagged endogenous model is also likely due to its empirically proven suitability to assessing short- and long-run elasticities (Prosser 1985; Sterner and Dahl 1992) and the higher level of complexity involved in modeling multiple lagged variables. More discussion on lagging is included in Section 5.3.3.

2.2.3 Data Types and Analysis Techniques

The type of data used in any given model depends on the model purpose and level of data that is available. There are three basic classes of data used for gasoline consumption modeling: **time series** - observations for one unit (e.g. household or location) over many periods; **cross-section** - observations for many units over one period; and **panel** - observations for many units over many periods (also referred to as longitudinal and cross-section time series (CSTS) data).[9] Panel and time-series were the most common data types used in models identified by this literature review.

It is important to note that cross-sectional data is static; there is no change over time. Therefore, a model based on cross-sectional data will likely not offer a set of clear and distinct short- or long-run elasticities. Rather, it will provide intermediate-run elasticities, like a static model, and may fail to distinguish the effect of geographic or demographic heterogeneity. Researchers agree that this inherent specification bias makes cross-section estimates generally unreliable (Goodwin 1992; Pesaran and Smith 1993; Basso and Oum 2007). The benefit of cross-sectional datasets is the greater heterogeneity in exogenous characteristics, which have been shown to influence fuel consumption considerably (see Section 5.5). A few examples of fuel consumption models based on cross-sectional data include: Ke and McMullen 2016; Karathodorou, Graham and Noland 2010; Wheaton 1982; and Drollas 1984.

Panel data provides the opportunity to examine heterogeneity across observational units in addition to adjustment to change in the explanatory variables over time. There are several techniques for using panel data, the most common being **pooled**, **fixed effects**, and **random effects** approaches. The appropriate choice of technique depends on the data set, underlying theory, and modeling goals; various statistical tests are used to determine whether the data and model specification adhere to the assumptions, described below, for each approach.

The pooled regression model ignores the structure of the data and assumes that the coefficients (both intercept and slope terms) are common across observational units and time. Pooling assumes homogeneity and ignores unique characteristics of each geographic region. The fixed effects model assumes that variation across units, or between observations in time, is correlated with the explanatory

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[7] Also known as a partial adjustment model

[8] Dynamic models which use multiple independent variables and lagged values of the dependent variable are distinguished from time-series analyses, or autoregressive models, which use solely lagged endogenous variables to forecast future values.

[9] The terms panel and longitudinal data often refer to data sets that include a relatively large number of observational units over a few time periods, while CSTS is often used to refer to data sets with relatively few observational units over many time periods. In this paper, panel data refers to data sets of any size with both cross-sectional and time dimensions.

variables and can be captured with differences in the constant (intercept) term.[10] This may be accomplished through the incorporation of dummy variables[11] for each observational unit or time period (less one, which represents the reference).[12] In the random effects model, differences among observational units are assumed random and uncorrelated with the explanatory variables.

Fixed effects estimation controls for unobserved heterogeneity (e.g. where the explanatory variables do not capture important geographic differences), thereby helping to remove omitted variable bias. For example, Coglianese et al. (2015) implemented time fixed effects in their panel analysis to account for variations (e.g., seasonal) that are the same across all states. Burke and Nishitateno (2013) incorporated geographic fixed effects to account for time-invariant gasoline price heterogeneity for different countries. However, Pesaran and Smith (1993) find that this technique doesn't fully address heterogeneity issues and recommend employing individual time series regressions if using a dynamic model. Goodwin et al. (2004) find similar difficulties with heterogeneous panel data use in dynamic models. Further investigation on modeling gasoline consumption using panel data (e.g., selecting a proper regression estimator and interpreting results) can be found in Baltagi and Griffin (1983).

Geographically aggregated time-series data has been very popular in the past since a large portion of policies focus on national-level implementation. Some authors have questioned the use of time-series data, though, due to its often non-stationary nature (e.g., (Bentzen 1994; Samimi 1995; Eltony and Al-Mutairi 1995). This is partially addressed in Section 5.3.2, with cointegration methods.[13] Based on their study of cointegration methods and consideration of the disadvantages inherent to cross-section and panel data, Basso and Oum (2007) suggest that time series relations are likely the optimal data type for calibrating gasoline consumption models.

More recent research has focused on elasticity heterogeneity and how to incorporate a broader range of such differences in gasoline consumption modeling. Approaches to addressing heterogeneity through data disaggregation are discussed in Section 5.5.

2.2.4 Functional Form

A model's functional form specifies the relationship between the dependent and explanatory variables and can restrict interactions between parameters of each explanatory variable. Unfortunately, terminology for functional form is inconsistent in the literature. In this paper, we adopt the terminology in Gujarati (1992) and Greene (1993) as described below.[14]

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[10] For example, month fixed effects may be used to account for seasonality when the magnitude of variation over a year is expected to be constant over time.

[11] Dummy variables, also known as indicator variables, take on the value of zero or one and are used to indicate presence of a characteristic or inclusion in a category.

[12] This approach results in the least squares dummy variable (LSDV) estimator. An alternative approach transforms the variables to deviations from the time averaged means (the fixed effects or *within* transformation).

[13] If both the explanatory and dependent variables are trending in time, it is possible that there is a high level of correlation between them. However, it is also possible that each is separately correlated to a third trending variable rather than being correlated to each other. *Cointegration* methods are used to identify such correlation and improve model reliability.

[14] This terminology is used consistently wherever the functional form of a reviewed model is described. However, the reader is cautioned that the sources included in the bibliography sometimes use terminology that is not consistent with these definitions.

Several different functional forms were found in the literature, including: linear, log-linear,[15] semilog, translog,[16] and non-linear. Log-linear models, which are linear in the natural logarithms of both the dependent and independent variables, are particularly popular because the coefficients can be directly interpreted as elasticities. In other words, a coefficient of the log-linear model measures the percent change in the dependent variable for a one percent change in the corresponding independent variable. The semilog model has two forms, the *log-lin* (only the dependent variable appears as a log) and the *lin-log* (only the independent variables appear as logs). The coefficients of the log-lin model indicate the percent change in the independent variable for a unit absolute change in the dependent variable. Conversely, the lin-log coefficients indicate the absolute change in the dependent variable for a one percent change in the logged variable. Table 1 illustrates common functional forms assuming a reduced form model, though these functional forms are also applicable to structural models.[17]

Table 1: Illustration of common functional forms for gasoline consumption models

Linear	$G = \alpha + \beta_1 P + \beta_2 Y$
Log-linear	$\ln G = \alpha + \beta_1 \ln P + \beta_2 \ln Y$
Semilog Log-lin Lin-log	 $\ln G = \alpha + \beta_1 P + \beta_2 Y$ $G = \alpha + \beta_1 \ln P + \beta_2 \ln Y$
Translog	$\ln G = \alpha + \beta_1 \ln P + \beta_2 \ln Y + \beta_{12} \ln P \ln Y + \beta_{11} (\ln P)^2 + \beta_{22} (\ln Y)^2$

Past studies have shown that economic theory often does not provide guidance on choosing the optimal form (Pace 1998; Schmalensee and Stoker 1999; Wadud 2007), but statistical test (e.g., Box-Cox) results and a long history of usage have led researchers to prefer log-linear specifications. It is important to note that, since the regression coefficients can be directly interpreted as elasticities, the log-linear form restricts each elasticity of demand to be constant through all values of both the independent and dependent variables. Meanwhile, other forms (e.g. semilog, linear, or trans-log specifications) result in elasticities that vary with the magnitude of their respective variable or the demand. Trans-log forms offer particularly flexible elasticities which can vary both in sign and magnitude through inclusion of logged variables in both linear and squared factors.[18]

Further exploration of functional form was relatively sparse until the late 1990s and early 2000s when researchers began to investigate more flexible functional forms like nonparametric and semiparametric techniques (Hausman and Newey 1995; Schmalensee and Stoker 1999; Coppejans 2003). These techniques help to reduce specification error, generally at the cost of efficiency (Pace 1998). More recent research (Blundell, Horowitz and Parey 2012; Liu 2014; Blundell, Horowitz and Parey 2016) seeks to make these functional forms more usable for gasoline demand modeling (see Section 5.3.1 for more discussion on these forms).

[15] Also called double-log or log-log

[16] Also called log-quadratic.

[17] See more discussion on functional forms in Wadud (2007) and Gujarati (1992).

[18] Wadud (2007) discusses gasoline consumption model functional forms fairly extensively.

3 STEO Gasoline Consumption Module Description

The Short-Term Energy Outlook (STEO) generates short-term monthly forecasts of U.S. supplies, demands, imports, stocks, and prices of various forms of energy using the Short-Term Integrated Forecasting System (STIFS) model. The first STEO was published in 1984 and the model has undergone numerous changes and modifications over the years (EIA 1984). One of the sub-models within this framework forecasts gasoline consumption for 12-24 months into the future.

STEO does not forecast gasoline consumption directly, rather it forecasts gasoline “product supplied,” which is a measure commonly used by EIA as proxy for consumption. EIA defines *gasoline product supplied* as "deliveries from primary suppliers, including refineries, blenders, pipelines, and bulk terminals." *Deliveries* are products supplied, shipments and/or disappearance from supply.

STEO forecasts future gasoline consumption on a monthly basis with a structural model that uses two regression equations to determine the influence of explanatory variables on vehicle miles traveled (VMT) and per-vehicle fuel efficiency (in miles per gallon, or MPG). Gasoline consumption is the quotient of the forecasted VMT and the forecasted MPG. Figure 1 below provides an overview of how the inputs (in green) feed into the model. The input sources are shown in italics underneath the variable name and description.

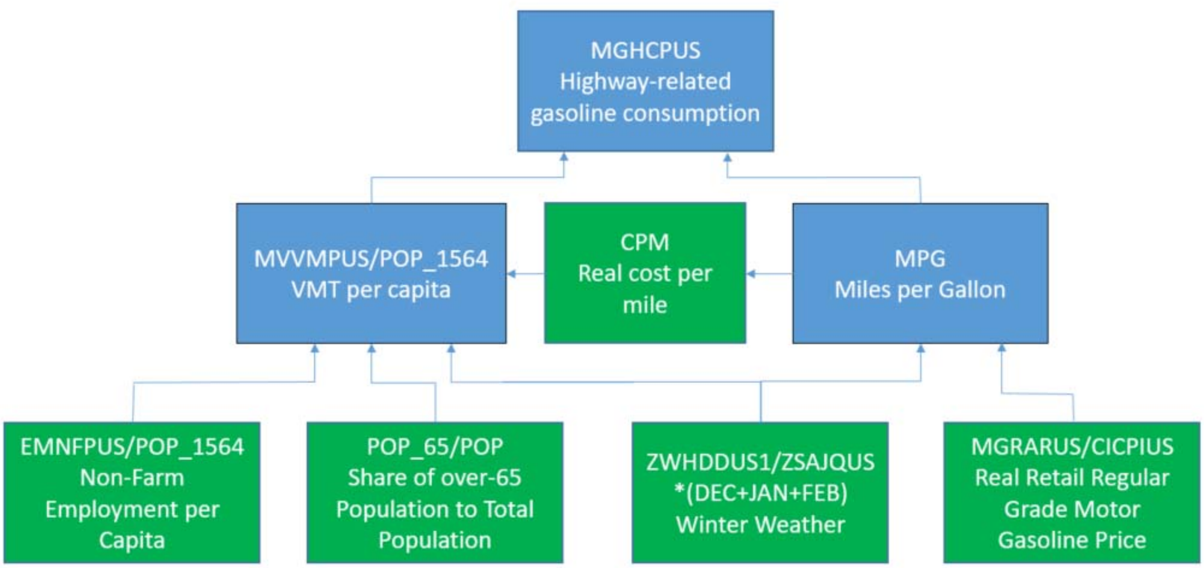

Figure 1: Flowchart indicating the basic structure of EIA's STEO gasoline consumption module.

Table 2 below provides a summary of the explanatory variables used in the model along with their sources.

Table 2: Data sources for EIA's STEO gasoline consumption module.

Dependent Variable	Explanatory Variable	Forecasted Data source
VMT per capita (includes diesel VMT)	Non-farm employment	IHS GI model
	Share of total population over age 65	IHS GI model
	Weather[24]	NOAA

	Real cost per mile[19]	IHS GI model[20]
Fuel economy (MPG)	Weather[24]	NOAA
	Real Retail Regular Grade Motor Gasoline Price	EIA[21]

The STEO model uses several dummy variables, labeled *shift variables*, to account for outliers likely caused by infrequent and unpredictable events (e.g., hurricanes, survey error, and other factors).[22] EIA STEO generally uses shift variables when the estimated regression error is more than twice the standard error of the regression. EIA does not attempt to determine the actual mechanisms/factors behind the outliers. The dummy variables are either monthly (form: Dyymm), annual (form: Dyy), or indicate a structural data shift after a certain date (form: DyyON).

The following two regression equations estimate vehicle distance traveled per capita and fuel efficiency using the independent variables listed in Table 2, along with the dummy variables discussed above.

3.1 Vehicle miles traveled per capita (MVVMPUS_SA/POP)

$$\begin{aligned}\log(\mathrm{MVVMPUS\_SA/POP\_1564}) = {} & a_0 + a_1 \log(\mathrm{EMNFPUS/POP\_1564}) \\ & + a_2 \log(\mathrm{CPM\_SA}) + a_3 \log(\mathrm{POP\_65/POP}) \\ & + a_4 \log(\mathrm{ZWHDDUS1/ZSAJQUS})*(\mathrm{DEC+JAN+FEB}) \\ & + a_5 (\mathrm{D14ON}*@\mathrm{trend}(2013{:}12)),\end{aligned}$$

VMT per capita is estimated using a log-linear regression on non-farm employment per capita (EMNFPUS/POP_1564), cost of gasoline (seasonally adjusted, CPM_SA),[23] population over 65 as a share of total population (POP_65/POP), a weather term ((ZWHDDUS1/ZSAJQUS)*(DEC+JAN+FEB)),[24] and a trend variable to account for an upward trend in highway travel for reasons other than those indicated by the existing explanatory variables (D14ON*@trend(2013:12)).

3.2 Fuel efficiency (MPG_SA)

$$\begin{aligned}\mathrm{MPG\_SA} = {} & b_0 + b_1 (\mathrm{D09ON}*@\mathrm{trend}(2008{:}12)) \\ & + b_2 (\mathrm{ZWHDDUS1/ZSAJQUS})*(\mathrm{DEC+JAN+FEB}) \\ & + b_3 (\mathrm{MGRARUS\_SA/CICPIUS}),\end{aligned}$$

[19] Calculated using MPG, retail regular-grade gasoline price including taxes, and consumer price index for all-urban consumers (1982-1984 = 1)

[20] Source for the all-urban consumer price index

[21] EIA *Monthly Energy Review* and *Weekly Petroleum Status Report*

[22] The shift variables take on a value of one for the time sample of the disturbance and a value zero in all other samples. Alternate terms for this application are impulse intervention, pulse, and blip variable. This contrasts with the use of dummy variables as step interventions that take on a value of one for a longer period of time (often all observations after a certain date) to account for structural or regime shifts such as implementation of a policy.

[23] Inflation-adjusted cost per mile (CPM) is calculated using the monthly average retail regular-grade gasoline price including taxes (MGRARUS, cents per gallon) and the consumer price index for urban consumers (CICPIUS, =1.00 for 1982-1984). Cost per mile is then seasonally adjusted (CPM_SA) using the seasonal factor derived from Census X-11 (an ARIMA method developed by the U.S. Bureau of the Census).

[24] The weather term captures the effects of colder-than-normal weather during winter months, which may depress highway travel.

Fuel efficiency is estimated using a linear regression on a trend term that incorporates time-dependent fuel efficiency trends like CAFÉ standards (D09ON*@trend(2008:12)), a weather term ((ZWHDDUS1/ZSAJQUS)*(DEC+JAN+FEB))[24], and real retail regular grade motor gasoline price (MGRARUS_SA/CICPIUS).

4 Prior Work

This section summarizes the initial literature review and *Short-term Domestic Gasoline Consumption Modeling Workshop* which took place January 30, 2017 in Washington D.C. This prior work focused primarily on price and income elasticity of gasoline demand (Z, INC. 2017). Additional findings on price and income elasticity from the literature review performed for the current work are included in Section 4.3.

4.1 Workshop Summary

The workshop brought relevant stakeholders together to collaboratively inform EIA's short-term gasoline consumption modeling efforts. The workshop included three different panel sessions: *Price Elasticity of Demand*, *Income Elasticity of Demand*, and *Fuel Efficiency, Driver Population, and Vehicle Characteristics*. Each panel discussion included presentations by technical experts on the subject.

The workshop concluded with a group discussion on recommendations for EIA and their future research on gasoline consumption modeling. Participants reached a consensus that the following should be reviewed: VMT input variables (e.g., mileage data), seasonal variation methods, data base year, and static versus dynamic data usage. Additionally, the participants recommended that EIA consider utilizing the following; ARIMA model, regional data, and statistical analysis using instrumental variables. It was also noted that EIA should review models dating before 2004 to see how they would work in an era of low gasoline prices. Lastly, from a social standpoint, the panel recommended that EIA consider developing STEO 'users groups'. Table 3 documents all of the recommendations expressed by the workshop participants.

Table 3: Summary of information and recommendations from EIA gasoline consumption modeling workshop participants

Name	Affiliation	Takeaway Points
Kenneth Gillingham	Yale University	• Described his work with vehicle registration data in Pennsylvania and California. He found that during times of gasoline price shocks, consumers drove less in response to the higher prices. He found that drivers in urban areas with access to public transportation were more responsive to higher gasoline prices. He found the medium-run price elasticity between -0.1 and -0.25. • Suggested using regional data when it is available, based on his research on various regional differences in data from CA and PA. • Look at uses of gasoline beyond those used in transportation. EIA used to do this; however, it was found to be an extremely small quantity that did not improve the accuracy of the estimates. The current STEO model no longer includes separate estimating of non-transportation gasoline.

Scott Irwin	University of Illinois	• Described his work in forecasting gasoline demand for estimating ethanol usage. He showed graphs of U.S. gasoline consumption from 1990 to 2016, VMT, and vehicle miles per gallon (MPG). He noted that the period from 1990 to 2004 had gasoline consumption very predictably rising. However, the graph subsequently flattened out before appearing to rise again in 2016. • Discussed his research with agricultural forecasting, which utilizes the ARIMA model. • Modeling beats experts' predictions in forecast accuracy. • Composite forecasting can combine ARIMA with another model. The results should be compared to see how they differ. • User feedback on a model's estimates could be helpful. • Comparing gasoline price growth to GDP growth is a useful measure. • Discussed how gasoline price as a percentage of GDP effects peoples' behavior (gasoline cost to GDP is around 2% right now)
Cynthia Lin Lawell	University of California at Davis	• Presented her findings on four issues: (1) distinguishing between supply and demand; (2) gasoline price volatility affecting the price elasticity of demand for gasoline; (3) consumers being more elastic in the long-term; and (4) the importance for policy, such as gasoline taxes. She said that as prices become more volatile, consumers are less responsive to changes in gasoline price. • Discussed statistical analysis using instrumental variables, which are known to affect the independent variable alone without directly affecting the dependent variable. This is achievable in differentiating between supply and demand. A price instrument is necessary that is correlated with price, but that is not in the demand equation. This could also be done with a combination of various countries energy costs.
Wewei Liu	Texas Christian University	• Described her work on income elasticity estimates using various statistical techniques. She showed graphs of the distribution of estimates with substantial heterogeneity, running from 0.05 to 0.3. She found that higher income leads to lower income elasticity. She also found that a higher gasoline price leads to higher income elasticity.
Lizbeth Martin-Mahar	Washington State DOT	• Discussed her office's use of the X-13ARIMA-SEATS seasonal adjustment software from the Census Bureau. They use E-views for the ARIMA (Auto Regressive Integrated Moving Average) model for their short-term monthly model of gasoline consumption. This model includes history and forecasts, a trend component, and a seasonal component. She noted that it sometimes produced overly optimistic projections of gasoline consumption and gasoline tax revenues, and they have had to interpret results accordingly. They only use ARIMA for forecasts for time periods of up to two years. Beyond two years, they use a long-term quarterly model, which includes fuel efficiency, non-farm employment, and gasoline pricing.
B. Starr McMullen	Oregon State University	• Discussed her work in examining the causal relationship between income and vehicle miles traveled (VMT). She found, through statistical analysis, that higher income causes an increase in VMT. She also described other studies she had done regarding VMT, especially in the state of Oregon, which showed differences between specific geographic regions. She noted that in Portland, people tend to drive more fuel efficient cars. • Based on her regional findings on VMT in Oregon, she observed that some states may be overestimating VMT when they forecast their gasoline tax revenue. • EIA should continue incorporating income data into STEO. Personal income, which is correlated to GDP, is important in gasoline consumption analysis.

Group Observations and discussion	• There was discussion about the number of people and vehicles in households, and how multi-vehicle households often just switch to the more fuel efficient car during price increases. • It is important to consider the frequency of price fluctuations • Model forecasts work well for 6-8 quarters into future and the periodic changes in models from seasonal variation were discussed. • It is important to work with a stable time period in addition to a varied time period. • An economic model can generally pick up new developments more quickly than ARIMA. • How should regional data fit into EIA's efforts? EIA has GDP data for metropolitan areas but it is only annual. Both Gillingham and McMullen have analyzed regionally disaggregated state data. Consensus was that data with different limits of aggregation have their own uses for various purposes. • EIA could consider using a different base year for data (currently 2005). • EIA should look at models that use data before 2004 to see how they would work in an era of lower gasoline prices. • Mileage data used in STEO should be reviewed; participants cited problems in delays in receipt of updates from DOT. In addition, VMT data from DOT often have revision. • The group discussed having an EIA STEO user group with regular meetings.

4.2 Prior Literature Review Coverage

The initial literature review and workshop report is divided into three sections consistent with the workshop panels: *Price Elasticity of Demand*, *Income Elasticity of Demand*, and *Fuel Efficiency, Driver Population, and Vehicle Characteristics* (Z, INC. 2017). The three sections analyze 27 publications that cover methods for estimating historic price elasticities, income elasticities, and other determinants of gasoline consumption. These are split between two different time periods: 1950-1999 and 2000-present. Much of the literature reviewed was oriented toward price or income elasticities of past data, rather than forecasting.

Sections 1 and 2 of the report feature a short synopsis of each paper including its purpose and results in the form of elasticity averages. The resulting elasticities are summarized in one comprehensive table (an updated version is provided in Table 4). Overall, price and income elasticities have seemingly become less and less responsive over time.

Other Determinants of Gasoline Demand

Section 3 of the initial report covers factors other than price and income elasticity in gasoline consumption modeling. These factors include fuel efficiency, driver population, and vehicle characteristics. The Fuel Efficiency section covers six studies that explicitly incorporate fuel efficiency data into their models, similar to EIA's STEO gasoline consumption module and concludes that "The pattern for phasing in fleet fuel economy improvements over time has been recognized in EIA's gasoline consumption modeling." The Driver Population section covers three studies that incorporate household panel data. One significant takeaway message was that elderly drivers have less annual mileage and that EIA has taken this into account in the Short-Term Motor Gasoline Consumption Module by including non-farm employment for ages 15 to 64 to account for the reduced mileage driven by elderly drivers." Lastly, the Vehicle Characteristics section overviews four studies that include data such as vehicles per household, age of vehicles, and types of vehicles.

The bulk of the initial report reviewed literature on price or income elasticities based on historical data, rather than short-term gasoline consumption forecasting. EIA has observed the trends in price and income elasticity of demand and has continually updated its models accordingly. Similarly, EIA has observed the literature on fuel economy and driver factors in modifying the models and incorporated the ideas from the literature reviewed in the initial report. Thus, the initial literature review did not present models that offer new approaches applicable to EIA's STEO forecasts. Overall, the report offered an in-depth review of price elasticity of demand and stands as a valuable resource for the price and income elasticities in gasoline consumption models.

4.3 Additional Findings on Elasticities

The most recent and most comprehensive review of price and income elasticities of gasoline demand identified in the current literature search is Dahl (2012), which reviews 240 gasoline demand studies for more than 70 countries. Some other key elasticity surveys include: Dahl (1986); Dahl and Sterner (1991);[25] Sterner and Dahl (1992); Goodwin (1992); Espey (1998); Graham and Glaister (2002); Goodwin, Dargay and Hanly (2004); and Brons, et al. (2008). Table 4 below includes short-run,[26] long-run, and ambiguous (intermediate-term, medium-term, and unspecified) price and income elasticities from several studies identified in past work (Section 4.2) as well as this current effort. The scope of this review did not include an overarching meta-analysis (see Dahl (2012) or Goodwin, Dargay and Hanly (2004) for this and a much wider range of international elasticities).

The literature is relatively unclear on how (or if) elasticities obtained through different models with various levels of data aggregation can be compared. Graham and Glaister (2002) suggest that much of the variation between elasticity estimates is due to researchers' use of different restrictive functional forms, and Wadud, Graham, and Noland (2010) suggest that elasticities from disaggregate data models should be compared to intermediate-run elasticities from aggregate data models. Regardless, to provide the broadest coverage possible, all the identified elasticities are shown together in Table 4.

[25] This study is particularly useful because it breaks down the elasticities by model type, data type, and data period.
[26] Sterner and Dahl (1992) define short run adjustments to be in time periods of a month, quarter, or year. No consensus exists regarding the time period limits for *short run*, as it often depends on the periodicity of the data. Goodwin (1992) suggests that short term likely refers to a period less than one year long. Archibald and Gillingham (1980) define short run as "the period within which a household's automobile stock and demographic profile fixed." (Lin et al. (1985) offer a similar definition).

Table 4: Compilation of price and income elasticities of gasoline demand from the literature.

Studies in green were found in the initial search and the remainder were found in the final stage of the project.
P = price elasticity; Y = income elasticity; subscripts "sr" and "lr" indicate short-range and long-range, respectively.

Author	Market	Date	Psr (lower)	Psr (upper)	Average				Ambiguous	
					Psr	Plr	Ysr	Ylr	P	Y
Brons 2008	USA, Canada, Australia	1978-2000							-0.530	
Cong. Budget Office 2008	USA; CA	1977-1989	-0.050	-0.080	-0.065					
Cong. Budget Office 2008	USA; CA	1994-2007	-0.020	-0.040	-0.030					
Dahl 2006	Industrialized countries	1966-1998			-0.350	-1.010	0.480	1.210	-0.880	
Dossary and Dahl 2009	International	1970-2005			-0.058	-0.182	0.142	0.444		
Espey 1998	USA, Canada, Europe, Australia, New Zealand	1966-1998			-0.260	-0.580	0.470	0.880		
Gillingham 2014	USA; CA	2001-2009							-0.220	
Gillingham 2015	USA; PA	2002-2010			-0.100					
Graham et al. 2002	International	1960-1998			-0.180	-1.000	0.180	1.000		
Hughes 2008	USA	2001-2006	-0.034	-0.077	-0.056					
Hughes 2008	USA	1975-1980	-0.210	-0.340						
Kayser 2000	USA	1981			-0.230		0.490			
Lin et al. 2013	USA	1999-2012			-0.068					
Litman 2017	Canada	2001-2006	-0.034	-0.077	-0.056					
Litman 2017	Canada	1973-1992				-0.643				
Liu 2014	USA	1994-2008			-0.062		0.175			
Manzan 2006	USA	1991-1994							-0.350	
Puller and Greening 1999	USA	1980-1990							-0.350	
Radchenko 2006	USA	1976-1997							-0.543	1.685
Schimek 1995	USA	1950-1994				-0.730		1.430		
Sterner 1992	World	1960-1998			-0.180	-1.000	0.180	1.000		
Wadud 2010	USA	1997-2002							-0.499	

Archibald and Gillingham 1980	US	1972-1973			-0.430		0.400			
Archibald and Gillingham 1981	US	1972-1973	-0.220	-0.772	-0.496		0.425			
Baltagi and Griffin 1983	18 OECD Countries	1960-1978				-0.725				
Basso and Oum 2007	Varies (lit review)	Varies	-0.200	-0.300	-0.250	-0.700	0.400	1.100		
Bentzen 1994	Denmark	1948-1991			-0.320	-0.410	0.890	1.040		
Blum et al. 1988	Germany and Austria	Varies	-0.250	-0.830	-0.540		1.380			
Burke and Nishitateno 2015	132 countries	1995-2008				-0.350				
Coglianese et al. 2015	US	1989-2008							-0.370	
Dahl 1982	41 countries	1970-1978			-0.200	-0.980	0.110	0.500		
Dahl 1986	Varies (lit review)	Varies			-0.210	-1.020	0.385	1.380		
Dahl 2012	Varies (lit review)	2006							-0.220	0.960
Dahl and Kurtubi 2001	Indonesia	1970-1995			-0.040	-0.630	0.190	1.290		
Dahl and Sterner 1991	Varies (lit review)	Varies	-0.220	-0.310	-0.265	-0.910	0.480	1.240		
Drollas 1984	US and 5 EU countries	1950-1980	-0.672	-0.157	-0.415	-0.922	0.386	0.865		
Elkhafif et al. 1993	Canada	1970-1990			-0.200	-0.590	0.333	0.480		
Eltony 1993	Canada	1969-1988			-0.310					0.150
Eltony and Al-Mutairi 1995	Kuwait	1970-1989			-0.370	-0.460	0.470	0.920		
Foos 1986	Germany	1968-1983			-0.280		0.250			
Gillingham and Munk-Nielsen 2016	Denmark	1998-2011							-0.300	
Goodwin 1992	Varies (lit review)	Varies							-0.280	
Graham and Glaister 2002	Varies (lit review)	Varies			-0.3	-0.700				
Greene 1981	U.S.				-0.100		0.350			
Hausman and Newey 1995	US	1979-1981							-0.810	0.370
Hunt and Ninomiya 2003	UK; Japan	1971-1997				-0.103		0.941		
Johansson and Schipper 1997	US	1973-1992							-0.700	1.200
Karathodorou 2010	US	1995							-0.475	0.130
Kouris 1983	US	1964-1981	-0.830	-0.110	-0.470	-0.665				
Lin et al. 1985	US	1966-1980	-0.106	-0.320	-0.213					
McRae 1994	11 Asian countries	1973-1987	-0.030	-0.500	-0.265		1.010			
Ramanathan 1999	India	1972-1994			-0.210	-0.320	1.180	2.680		
Schmalensee and Stoker 1999	US	1988-1991								0.210
Sterner et al. 1992	OECD; lit review	Varies	-0.180	-0.250	-0.215	-0.950	0.300		-0.675	1.063
Wachs et al. 2015	U.S.; Oregon	Unknown							-0.073	
Wasserfallen and Guntensperger 1988	Switzerland	1962-1985	-0.300	-0.450	-0.375		0.7			
Yatchew and No 2001	Canada	1994-1996							-0.900	0.290

The results shown in Table 4 confirm two well-established results from other literature reviews: long-run elasticities are generally larger than short-run elasticities,[27] and income elasticities are typically larger than price elasticities.

It should be noted that this information is not entirely applicable to EIA's STEO Gasoline Consumption model. Expanding this elasticity research to include elasticities not only of gasoline consumption, but also of car stock, VMT,[28] fuel efficiency, and other dependent variables used in the structural model literature would be highly valuable, especially for structural models like EIA's STEO. The short run price elasticity used in EIA's STEO VMT model is -0.031 and the STEO does not include an income explanatory variable. A few papers identified some of the work done in this area as shown in Tables 5 and 6. One interesting note is that most of the price and income effects on gasoline consumption are due to changes in vehicle distance traveled, especially in the short run.

Table 5: Price elasticities for vehicle distance traveled and fuel efficiency. [29]

Dependent variable	Price Elasticity range or average	Notes
Vehicle distance traveled	-0.292	Long-run average (using cost per mile) (Dahl 1979)
	1.9 to -2.25	Overall range (Dahl 1986)
	-0.21 to -0.50	Annual stock models[30] with non-household-level data (Dahl 1986)
	-0.32	Short-run average for stock models (Dahl 1986)
	-0.55	Long-run average for stock models (Dahl 1986)
	-0.157 to -0.610	Short-run range (Archibald and Gillingham 1980)
	-0.16; -0.32	Short-run; Long-run (P. Goodwin 1992)
	-0.06 ; -0.26	Short-run; Long-run (Schimek 1996)
	-0.05 to -0.35	Long-run average of multiple estimation techniques (Johansson and Schipper 1997)
	-0.15; -0.3	Short-run; Long-run (Graham and Glaister 2002)
	-0.10; -0.29	Dynamic models, literature review. Short-run; long-run (Goodwin, Dargay and Hanly 2004)
	-0.27 to -0.38	Static models, literature review. (Goodwin, Dargay and Hanly 2004)

[27] Recent work has suggested that short-run price elasticities may be biased toward zero, primarily because gasoline prices are positively affected by gasoline demand. This could create a spurious correlation between price and the regression error. Researchers are exploring the use of *instrumental variables* to act as a reasonable proxy for gasoline consumption (e.g., gasoline tax) in order to avoid this bias (Coglianese, et al. 2015; Stock and Yogo 2005; C. A. Dahl 1979).

[28] Modeling VMT is gaining interest due to the recent interest in VMT-based vehicle taxation (e.g., Oregon and Washington states). For a recent paper (including a literature review), see McMullen and Eckstein (2013).

[29] Archibald and Gillingham (1980) uses a model based on household-level data.

[30] Contain a vehicle variable but no lagged variables

	-0.153 to -0.169	Short-run; 2SLS model, 87 Urban areas (McMullen and Eckstein 2013)
	-0.3	Medium-run (Gillingham and Munk-Nielsen 2016)
Fuel efficiency	0.212	Long-run average (Dahl 1979)
	0.06 to 1.43	Overall range (Dahl 1986)
	0.17	Short-run average (Dahl 1986)
	0.57	Long-run average (leaving out extreme outliers) (Dahl 1986)
	0.062 to 0.162	Short-run range (Archibald and Gillingham 1980)
	-0.015 ; -0.602	Short-term; Long-term (Elkhafif and Kubursi 1993)
	0.05 ; 0.23	Short-run; Long-run (Schimek 1996)

Table 6: Income elasticities for vehicle distance traveled and fuel efficiency.

Dependent variable	Income Elasticity range or average	Notes
Vehicle distance traveled	0.15 to 0.66	Stock models (Dahl 1986)
	0.26	Short-run average for stock models (Dahl 1986)
	0.60	Long-run average for stock models (Dahl 1986)
	0.231 to 0.474	Short-run range (Archibald and Gillingham 1980)*
	0.07; 0.29	Short-run; Long-run (Schimek 1996)
	-0.1 to 0.35	Long-run average of multiple estimation techniques (Johansson and Schipper 1997)
	0.30; 0.73	Dynamic models. Short-run; Long-run (Goodwin, Dargay and Hanly 2004)
	0.46 to 0.55	Static models. (Goodwin, Dargay and Hanly 2004)
	0.142 to 0.343	Short-run; 2SLS model, 87 urban areas (McMullen and Eckstein, Determinants of VMT in Urban Areas: A Panel Study of 87 U.S. Urban Areas 1982-2009 2013)
Fuel efficiency	-0.07	Short-run average (Dahl 1986)
	-0.21	Long-run average (Dahl 1986)
	-0.063 to -0.081	Short-run range (Archibald and Gillingham 1980)*
	-0.01; -0.06	Short-run; Long-run (Schimek 1996)

*The elasticities for Archibald and Gillingham (1980) are Total Expenditure elasticities.

STEO uses a log-linear form with a price factor in its estimation of VMT. Dahl's research shows that the price and income elasticities of vehicle distance traveled and fuel efficiency are "less precise than the income and price elasticities of gasoline demand," attributing the lower precision to either difficult-to-predict consumer behavior, or just bad data (Dahl 1986). The literature generally agrees that there is some level of inter-dependence between price elasticity, income elasticity, changes in price, and changes in income, and oftentimes addresses this issue by using a different functional form (e.g., trans-log). The inter-dependency between, and heterogeneity of, price and income elasticities is discussed in Section 5.5 alongside a review of models based on disaggregated data.

One final consideration, specifically regarding price elasticities, is the symmetry to direction of change. Dahl (2012) started with the expectation that gasoline consumption will be more elastic with price *increases* (recoveries) than with price *cuts*, but her investigation of past literature found mixed evidence.

She concludes that there is a serious risk of overestimating price response in models that assume symmetry, and mentions the need for more research in this area.

5 Literature Review Findings

The first step in the literature review was to identify models that were generally similar to EIA's STEO: structural form with aggregated data. The analysis expands out from there, identifying model structures and approaches that differ from the STEO gasoline consumption model by varying degrees. This section discusses the key differences noted in the literature, first looking at use of different dependent and independent variables, followed by analysis of different traditional approaches, and finishing with discussion on models and data that are completely different from the STEO. Models using disaggregated data are then addressed separately in Section 5.5.

5.1 Considerations for Structural Models

The demand for highway motor gasoline is primarily derived from the demand for vehicle transport, which is the result of consumers' vehicle stock and characteristic choices.[31] Structural models (as opposed to reduced form models) specifically try to estimate this relationship, as can be seen in EIA STEO's breakdown of highway-related gasoline consumption into vehicle distance traveled and vehicle efficiency components. It is important to quickly review the different definitions for these three dependent variables.

Most of the literature specifically distinguishes between gasoline and diesel consumption (separate models based on separate explanatory variables, like STEO), although there are exceptions (e.g., (Lin, Botsas and Monroe 1985; Schimek 1996). Gasoline consumption can be disaggregated (e.g., total, per capita, per car, per household, per licensed driving) and reported as either a level or a percent change. The literature reviewed used the following measurements: aggregate level, per capita, per capita per day, annual percent change or per car, with the first two being most common.

EIA recently removed the non-highway related gasoline consumption component from the STEO model. Most of the literature either does not explicitly model non-highway related gasoline consumption or avoids modeling it altogether (e.g., household-level data models). For example, Dahl (1982) uses combined gasoline consumption, including all non-road use like aviation. In later work, Dahl (1986) finds that non-highway gasoline consumption is typically less elastic than highway gasoline consumption.

STEO does not explicitly differentiate gasoline consumption by vehicle type. Kouris (1983) separately models three gasoline consumption dependent variables: passenger cars, trucks, and buses/motorcycles/other, possibly an important differentiation since commercial vehicles tend to have a higher price elasticity of demand (Ramsey, Rasche and Allen 1975). Baltagi and Griffin (1983) add "truck per car" and "trucks per capita" variables to capture the effect of non-passenger car highway gasoline use, but found them to be statistically insignificant.

In most models, vehicle distance traveled (vehicle miles traveled, or VMT, in the U.S.) is measured on a per capita basis or is portrayed as an aggregate total. There is a wide range of literature specifically focused on estimating VMT which was not a primary focus of this review. However, the review did not identify any structural models that lacked a VMT component.

[31] The majority of literature assumes that gasoline demand is separable from the demand of other goods.

Basso and Oum (2007), a recent and highly cited literature review, suggests that researchers differ in their concepts of fuel efficiency. On one side, some researchers refer to vehicle fuel efficiency as a "technological characteristic of the car." Other authors use "fuel efficiency" to encompass not only these technological characteristics, but also the actual driving behavior and efficiency with which each mile is driven. Basso and Oum (2007) state that the latter adjustments "will occur in the short-run, for a given fleet of cars," generally in parallel with a short-run reduction in vehicle distance traveled, according to the literature) while the survey presented by Dahl (1986) and other work (Rouwendal 1996; Puller and Greening 1999) indicate that the fuel efficiency due to technological changes are introduced over the longer run. Kouris (1983) suggests using percent change in fuel efficiency to accurately capture the dynamic impact of technological progress. Accurate and reliable disaggregated data would be required to adequately address the variance in behavioral fuel efficiency responses. Schipper, et al. (1993) discuss in greater depth the nuances of fuel efficiency definitions and measurement approaches for gasoline consumption modeling.[32]

STEO's two-component structural approach is not common; in fact, most of the structural models add car/vehicle stock as a third component. Table 7 below summarizes the structural models in the literature, followed by a discussion of a few notable structural model results.

Table 7: Structural gasoline consumption models identified in the literature[33]

Source	Structural components	Explanatory variables	Additional notes
Dahl 1979	Vehicle distance traveled	Cost per mile Income Vehicle stock	Structural components are only modeled separately; not fed into a final equation
	Vehicle efficiency	Gasoline price Income Dummy (1968 pollution regulations)	
	Vehicle stock	Gasoline price Price of automobiles Income Lagged vehicle stock (lag 1)	
Kouris 1983	Vehicle distance traveled	Current gasoline price Past 9 lagged values of gasoline price	Modeled passenger cars and trucks separately.[34]
	Vehicle efficiency	Gasoline price Private consumption expenditure Vehicle stock	
Gallini 1983	Vehicle distance traveled	Gasoline price Income Unemployment rate	Several additional sub-models are contained within; the basic structure
	Car stock	Gasoline price Income	

[32] Also see Elkhafif and Kubursi (1993) for discussion and analysis on how policy and regulations affect fuel efficiency

[33] Elkhafif and Kubursi (1993) developed a unique structural model that only estimates 1 component (vehicle efficiency) and uses that as part of the gasoline consumption estimator.

[34] The truck VMT estimator includes an *index of industrial production*, *truck stock*, and *gasoline price.*

		Car price (by weight) Unemployment rate Lagged automobile holdings	is simplified in the interest of space.
	Vehicle efficiency	Price of gasoline (lag 1, 2, 3) Environmental controls (lag 1, 2, 3) Fuel economy standards (lag 1, 2, 3)	
Wasserfallen and Guntensperger 1988	Vehicle distance traveled	Consumer prices as a whole Real income Lagged car stock Relative gasoline price	
	Vehicle efficiency	Relative gasoline price Real income	
	Car stock	Relative gasoline price User cost of new cars Real income Quality of private traffic network Quality of public traffic network	
Schimek 1996	Vehicle distance traveled (per vehicle)	Real gasoline price Real GDP per capita Car stock per capita Vehicle fuel efficiency Time dummies Lagged endogenous (lag 1)	CAFE trend variable was required to reduce serial correlation
	Vehicle efficiency	Real gasoline price Real GDP per capita CAFE trend dummy	
	Car stock (per capita)	Real gasoline price Real GDP per capita Vehicle price	
Johansson and Schipper 1997	Vehicle distance traveled (per capita)	Cost of driving (composite of fuel price and vehicle efficiency) Income Taxation variable[35] Population density Car stock per capita Lagged endogenous (lag 1)	
	Vehicle efficiency	Fuel price Income Taxation variable[35] Population density Lagged endogenous (lag 1)	
	Car stock (per capita)	Fuel price Income Taxation variable[35]	

[35] A "sum of different kinds of purchase taxes and import fees plus the present value of the annual tax for a specific car, a medium-sized standard car of Volkswagen Golf type" (Johansson and Schipper 1997).

		Population density Lagged endogenous (lag 1)	
Puller and Greening 1999	Vehicle distance traveled	Price of gasoline (current and lag 1) Vehicle efficiency Real household income Price of maintenance goods and services Household characteristics (several)	Uses household-level data
	Vehicle efficiency	Price of gasoline Vehicle distance traveled Real household income Price of new vehicles Household characteristics (several)	
Karathodorou and Graham 2010	Vehicle efficiency	Gasoline price GDP Urban density Road length per 1000 people Public transport seat-km per capita Car user cost per car	
	Car stock	Gasoline price GDP Urban density	
	Vehicle distance traveled	Gasoline price GDP Car stock Vehicle efficiency Urban density Road length per 1000 people Public transport seat-km per capita Average user cost of public transport trip Car user cost per car	

In one of the earliest structural model applications, Kouris (1983) utilizes vehicle distance traveled and vehicle efficiency as structural model components. He also investigates the use of new car registrations and a lagged dependent variable for the fuel efficiency and VMT components, respectively, finding that both offered negligible explanatory value in the model.

Johansson and Schipper (1997) use a similar approach across a much wider dataset (12 countries), but add car stock per capita in addition to vehicle distance traveled and vehicle efficiency. Including car stock in the model specification helps to clarify the ambiguity in elasticity period which is inherent to cross-sectional data. The vehicle distance traveled is calculated using a *recursive* system approach, with distance traveled dependent on car stock and vehicle efficiency. This is similar to STEO's VMT calculation, which is dependent on the vehicle efficiency. Johansson and Shipper's model determined that vehicle stock is strongly dependent on national income, and considerably less dependent on gasoline price, while the elasticities for the vehicle efficiency calculation were lower in general. By incorporating a combined fuel price and vehicle efficiency variable (like EIA), the researchers save degrees of freedom.[36] The authors then substitute their parameters into the structural equation to obtain a reduced form equation where gasoline consumption is related to fuel price, income, taxation, and population density; this reduced form equation could help determine the price and income elasticities, while the structural sub models could decompose the elasticities into their sources. They find fuel demand to be relatively price inelastic but income elastic and their price and income elasticities of travel demand are close to that found in other surveys (see Table 5 and Table 6). Several other structural models implement car stock as a dependent variable: Karathodorou, Graham and Noland 2010 (specifically looking at urban density effects), Wheaton 1982, and Baltagi and Griffin 1983.

Gallini (1983) provides an example of a much more complex structural gasoline consumption model, as summarized in Figure 2 below. Gallini (1983) projects automobile manufacturers' fuel efficiency adjustments based on consumer responses to fuel price. This is accomplished using three lagged variables (for *t-1, t-2,* and *t-3*) that model a decrease in design flexibility as they approach commercialization (i.e., the current time step). Other endogenous variables, outside of the standard vehicle distance traveled and fuel efficiency, include stock of used cars per individual (including scrappage rate) and choice of new car (separate model with three vehicle options by weight). Most of the endogenous variables are modeled based on a utility maximization framework, which requires a relatively large amount of data. For example, the model requires prices for new and used cars (by weight and fuel efficiency) and man-days lost in the automobile industry due to strikes. Data is unavailable for some of the variables, and must be estimated.

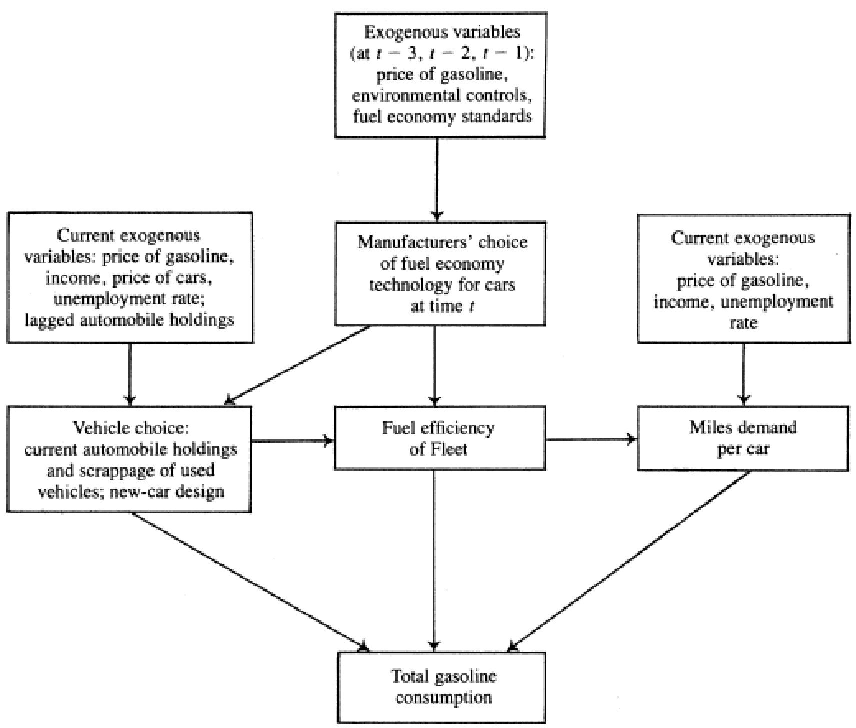

Figure 2: Gasoline consumption model structure from Gallini (1983).

[36] The paper's authors admit that this is not really an axiomatically correct assumption.

The extra effort enables Gallini's model to reveal even more characteristics of gasoline consumption, including for instance the appearance of the VMT rebound effect, where an increase in fuel efficiency leads to a decrease in cost per mile, followed by an offset to the initial reduction in vehicle distance traveled. Eltony and Al-Mutairi (1995) add an additional layer of complexity to Gallini's model, using the same model structure but replacing the aggregated data with household-level disaggregated data (discussion in Section 5.5).

The previous studies' results indicate that driving less (reduced vehicle distance traveled) is generally a short-run response, while vehicle fuel efficiency is a long-run response. As indicated in the table, several other structural models were identified in the literature.

5.2 Non-Structural Considerations

The next step in the review explored selection of explanatory variables, looking primarily for additions or alternatives to those found in EIA's STEO gasoline consumption module. In addition, the literature was reviewed for suggestions on different methods and approaches to measuring the dependent and independent variables found in the EIA model. This review did not include assessing how much of the literature generally validates the variable selection found in the EIA model.

5.2.1 Alternative Measures for Existing Explanatory and Dependent Variables

Table 8 below summarizes suggestions found in the literature on alternate definitions/measurements of EIA STEO's independent variables. Note that lagged versions of the variables are not included here but use of lagged exogenous variables are discussed in Section 5.2.2.

Table 8: Suggested alternative measures of existing EIA explanatory variables from the literature

Explanatory variable	Current Measure	Alternative Measures (and source)
Population	Total U.S. Population (millions)	Annual percent change, State, step ahead (Sillence 2014) Percentage of driving age (16-65), household, (Eltony 1993) Density[37]
Employment	Unemployment Rate	Non-agricultural employment, OR State (Wachs and Heimsath 2015), AZ State (Arizona DOT 2016), WA State (WA DOT 2010) Labor force participation, OR State, (Wachs and Heimsath 2015) Annual percent change in employment, State, step ahead (Sillence 2014) Per household, (Eltony 1993)
Price of gasoline	Price of gasoline	Change in price, (Coglianese, et al. 2015; Sillence 2014) Real producer prices of fuel (Lehbert 1977; Kriegsmann 1980[38]) Nominal gasoline price (Arizona DOT 2016; Teichmann 1983;[38] Drollas 1984)

[37] See discussion in Urbanization, Section 5.2.2.2

[38] Reviewed by Blum, Foos, and Gaudry (1988), not part of the literature review.

		Relative to other goods (Baltagi and Griffin 1983; McRae 1994) 4-year moving average (Elkhafif and Kubursi 1993)
Weather	Average HDD	(Foos 1986)[38] Temperature (Lehbert 1977),[38] (Hunt and Ninomiya 2003)
TREND	NA	(Tanner 2008;[38] Elkhafif and Kubursi 1993;[39] Schimek 1996;[40] Hunt and Ninomiya 2003;[41] Burke and Nishitateno 2013)

5.2.2 Possible Additional Explanatory Variables

Income, vehicle stock (Sterner and Dahl 1992; Graham and Glaister 2002), vehicle characteristics (usually fuel economy), and/or other socioeconomic variables are included as explanatory factors in some studies. Incorporating additional explanatory variables into gasoline consumption models (whether a reduced form gasoline consumption model, or reduced form VMT/fuel efficiency models that are part of a larger structural gasoline consumption model) tends to reduce the price and income elasticities. It is important to avoid potential bias due to the omission of a significant variable,[42] although simply adding variables into equations without any supporting theory is not good modeling practice (Sterner and Dahl 1992). This section reviews different variables used, suggested, and tested by publications in the literature. The focus is on aggregated data; further discussion of the variables used in disaggregate data based models (e.g., household-level demographics) is in Section 5.5.

5.2.2.1 Explanatory Variables Used in Existing Models

Table 9 below reviews several different explanatory variables that are used in the literature (in addition to those already used by STEO).

Most model structures identified in the literature utilize income as an explanatory variable, including all the structural models (see Table 7). Based on the literature, income offers statistically significant explanatory power for variation in gasoline consumption in a wide range of models. In fact, short- and long-run income elasticities are often larger than price elasticities (see Table 4 under Section 4.3).

Outside of income, vehicle characteristics were one of the most common investigated in the literature. Some form of vehicle stock characteristics may be used as a proxy for vehicle price since data on the latter may be difficult to obtain (Dahl 1982). Generally, variables like car stock or price can only be considered as long-run decisions and, therefore, the elasticities are inherently long-run (Dahl 1986). However, using a car stock or other vehicle characteristic variable may result in lower price and income elasticities (closer to short-run values) because these variables reflect consumer choices and are

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[39] Intended to cover "developments in basic science and technology, consumer preferences and long-term economic growth."

[40] Controls for the effects of the CAFE program (1978+)

[41] Includes discussion and analysis of the "underlying energy demand trend" and seasonality, using a time trend to account for "technical progress"

[42] For example, Blum, Foos and Gaudry (1988) suggest that not including certain economic variables will lead to an overestimation of income elasticity.

therefore partially dependent on both price and income (Basso and Oum 2007). In some cases, such as Archibald and Gillingham (1980), the model targets short-run estimates by holding car stock fixed.

As mentioned previously, this section and table do not include all the models based on household-level data (see Section 5.5).

Table 9: Suggested additional explanatory variables from models in the literature

Explanatory variable	Notes	Source[43]
Income	Real disposable income per capita	(Baltagi and Griffin 1983; Elkhafif and Kubursi 1993; Eltony and Al-Mutairi 1995; Marrero, Lorenzo-Alegria and Marrero 2012; McMullen and Eckstein 2013; Liu 2014)
	Per household	(Eltony 1993; Ke and McMullen 2016)
	GDP per capita	(Oldfield 1980;[38] Dahl 1982; Baltagi and Griffin 1983; McRae 1994; Schimek 1996; Ramanathan 1999; Dahl and Kurtubi 2001; Tanner 2008;[38] Karathodorou, Graham and Noland 2010; Burke and Nishitateno 2013)
	Real GDP	(Wasserfallen and Güntensperger 1988; Kriegsmann 1980;[44] Proske 1979)[38]
	Real aggregate personal income, OR State	(Wachs and Heimsath 2015)
	Nominal personal income	(Arizona DOT 2016)
Car stock	Elasticity with respect to gas demand: 0.42	(Dahl 1986)
	Elasticity with respect to gas demand: 0.34	(Tishler 1983)[38]
	Car stock per capita; 19 countries	(Baltagi and Griffin 1983)
	Car stock per capita; 41 countries; elasticities: 0.12 (short-run) and 0.57 (long-run)	(Dahl 1982)
	Car stock per capita; 11 countries	(McRae 1994)
	Number of gas vehicles per capita AND number of diesel vehicles per capita	(Marrero, Lorenzo-Alegria and Marrero 2012)
Vehicle stock (incl. trucks)	Elasticity with respect to gas demand: 0.53	(Dahl 1986)

[43] The variables investigated by Dahl (1986) were from a number of past publications (over 50). Dahl also discusses the elasticities of vehicle distance traveled and vehicle efficiency for each independent variable investigated.
[44] Reviewed by Blum, Foos and Gaudry (1988), not part of the literature review.

	Lagged stock of vehicles	(Reza and Spiro 1979)[38]
Vehicle fuel efficiency	Elasticity with respect to gas demand: 0.61	(Blum, Foos and Gaudry 1988)
	Lagged weight of new cars	(Reza and Spiro 1979)[38]
	Of existing OR State stock; elasticity with respect to gas demand: -0.13	(Wachs and Heimsath 2015)
	Of AZ State	(Arizona DOT 2016)
	Of MO State; elasticity with respect to gas demand: -0.49	(HDR/HLB 2007)
Real diesel price	Not for a combined gas/diesel model	(Marrero, Lorenzo-Alegria and Marrero 2012)
Composite gas price and fuel efficiency		(WA DOT 2010)
Car price	Elasticity with respect to gas demand: 0.32	(Dahl 1986)
	Real price of vehicles	(Drollas 1984)
Prices of consumer goods		(Foos 1986)[38]
	"all other goods"	(Drollas 1984)
Private consumption expenditure	Per capita	(Houthakker and Taylor 1966)
	Total	(Kouris 1983)
Consumer sentiment index	OR State	(Wachs and Heimsath 2015)
Public transportation	Real price of transport services	(Drollas 1984)
Road Saturation	Number of vehicles per km of road	(Marrero, Lorenzo-Alegria and Marrero 2012)
Urbanization	See discussion following Table 10	Numerous
Seasonal component	Compared performance to TREND component	(Hunt and Ninomiya 2003)
Lagged endogenous	Single lag	(Lehbert 1977;[38] Fotiadis, et al. 1980;[38] Houthakker and Taylor 1966; Houthakker, Verleger and Sheehan 1974; Verleger and Sheehan 1976;[38] Mehta, Narasimham and Swamy 1978; Kwast 1980; Berzeg 1982; Baltagi and Griffin 1983; Dahl 1982; Eltony and Al-Mutairi 1995; HDR/HLB 2007; Marrero, Lorenzo-Alegria and Marrero 2012)
	Lag 1 and 2	(Drollas 1984)
	Lag 1, 2, and 3	(Dossary and Dahl 2009)
Lagged exogenous	Income twice, gasoline price twice	(Drollas 1984)
	Income once, relative gas price once	(Baltagi and Griffin 1983)
	Current and 9 lagged values of gas price	(Kouris 1983)
	GDP once, gas price twice	(McRae 1994)

	3-quarter moving average of income, 4-year moving average of gas price	(Elkhafif and Kubursi 1993)
	Polynomial lag of GDP and real price of oil	(Hunt and Ninomiya 2003)
	Income twice, gasoline price twice	(Dossary and Dahl 2009)
	Lag 1 and Lead 1 change in gasoline price	(Coglianese, et al. 2015)

5.2.2.2 Additional Explanatory Variables Investigated in the Literature

A few studies suggest and explore the effects of other explanatory variables that they don't include in their models. Table 10 provides a partial listing of these additional suggestions. Two concepts, effect of urban density and use of dummy variables, are discussed further below.

Table 10: Explanatory variables suggested and/or tested by researchers in the literature.

Explanatory variable	Notes/Findings	Source
Number of Households	Increased faster than the population in past decades	(Basso and Oum 2007; Sillence 2014)
Proportion of people of driving age	Increased faster than the population in past decades	(Basso and Oum 2007)
Population by age cohort		(Sillence 2014)
Vehicle registrations	Statewide	(Sillence 2014; WA DOT 2010)
State trunk network lane miles		(Sillence 2014)
Public transportation service accessibility, levels, and costs	Modal shifts may affect long-term car ownership more than assumed	(P. Goodwin, A Review of New Demand Elasticities with Special Reference to Short and Long Run Effects of Price Changes 1992)
Urbanization	See discussion following this table	Numerous
Retail sales	Statewide	(Sillence 2014)
Consumer sentiment	Statewide; came out as insignificant	(WA DOT 2010)

Urban Density

Newman and Kenworthy (1989) collect fuel consumption data for 32 cities in Europe, Canada, Asia, Australia, and the U.S. and find that there is a strong negative correlation between urban density and fuel consumption per capita. The correlation persists after adjusting economic variables (income, prices and vehicle efficiencies) in each country to match the U.S. Further studies by Kenworthy and Laube (1999), Cameron, Kenworthy and Lyons (2003), Mindali, Raveh and Salomon (2004), van de Coevering and Schwanen (2006), and Shim, et al. (2006), explore the dependence more rigorously using econometric regression models or dimensional analyses. The consensus (outside of the results from Mindali, Raveh and Salomon (2004)) is that increased urban density is associated with reduced fuel consumption.

Johansson and Schipper (1997) mention that population density or urbanization will have different effects on gasoline consumption depending on whether aggregate (nationwide or state-wide) data or disaggregate (municipality or household-level) data is used, but that in general “population density seems to affect fuel demand in a non-negligible way.”

A more recent study of the relationship between urban density and fuel demand finds that urban density does affect fuel consumption, mostly through variations in the car stock and in the distances travelled, rather than through fuel consumption per kilometer (Karathodorou, Graham and Noland 2010). Semi-parametric analysis in Liu (2014) identifies urban form (population density) as having a strong impact on gasoline demand at the state level. Gillingham and Munk-Nielsen (2016) conclude that the price elasticity heterogeneity due to urbanization is heavily impacted by “two tails of more responsive drivers than most of the population.” The first tail includes drivers who live in the city outskirts with long commutes but have adequate access to public transportation, and the second includes drivers who live in the city but with short commutes. The price elasticity of VMT is much greater for these two groups than for much of the population. They posit that their results, which are for Denmark (widespread access to public transportation), likely don’t apply to the United States; the first “tail” doesn’t exist in the U.S. because of the less-expansive public transportation system.

Work by Banister and Banister (1995) also concludes that local urban density and form affect modal choice, vehicle use, and total travel demand. Other prominent literature that suggest considering such a term, either based on a review or on their own modeling and analysis, include Archibald and Gillingham (1980); Archibald and Gillingham (1981); Greene (1981); Lin, Botsas and Monroe (1985); Dahl (1986); Hausman and Newey (1995); Puller and Greening (1999); Schmalensee and Stoker (1999); Kayser (2000), Wadud (2007), Burke and Nishitateno (2013), Dahl (2012), and Sillence (2014). All of them find that urbanization (called “metropolitanization” by Liu (2014)) significantly impacts gasoline consumption.

There is a wide range of conclusions on price and income elasticity variation due to urbanization level. One interesting point made by Yatchew and No (2001) (using household-level data) is that the price variation within given rural or urban areas is high and, as a result, those who drive more in these areas will encounter more price options and likely pay less for gasoline. Therefore, in a model where vehicle distance traveled or level of gasoline consumption are dependent variables, it is possible that the price coefficient could be consistently overestimated when including an urbanization variable. Wadud, Graham, and Noland (2010) review recent work and analyze some of the variation within and between rural and urban households. Table 11 illustrates that, even though rural and urban gasoline consumption clearly responds differently to price and income, adjustments in demographic variables play a key role in determining *how much* different the elasticities are.

Table 11: Effects of urbanization, car ownership, and wage earners per household on price and income elasticities. Source: (Wadud, Graham and Noland 2010)

Household characteristics			Elasticities (first value uses national price & income average; second uses the group averages)	
Location	**Car ownership**	**Wage earners**	**Price**	**Income**
Urban	Single	Zero/one	-0.341; -0.414	0.273; 0.329
Urban	Single	Multiple	-0.425; -0.401	0.314; 0.304
Urban	Multiple	Zero/one	-0.493; -0.484	0.373; 0.365
Urban	Multiple	Multiple	-0.577; -0.490	0.414; 0.351
Rural	Single	Zero/one	-0.091; -0.236	0.297; 0.391
Rural	Single	Multiple	-0.175; -0.238	0.338; 0.362
Rural	Multiple	Zero/one	-0.243; -0.325	0.397; 0.445
Rural	Multiple	Multiple	-0.327; -0.321	0.438; 0.423

Note: Total household expenditure used as a proxy for income.

Expanding on past investigation into the effects of urban areas on VMT, McMullen and Eckstein (2013) and Ke and McMullen (2016) indicate that an urban/rural categorization is a good first step but is insufficient and needs further disaggregation to achieve better understanding (in agreement with Wadud, Graham, and Noland data shown in Table 11).

Dummy Variables: Fixed Effects, Pulse, and Step Interventions

As discussed in Section 3, the STEO model utilizes dummy variables as pulse interventions to address data outliers attributable to infrequent and unpredictable events; the model does not attempt to explain the underlying mechanisms. Dummy variables can also be used to account for data methodology, policy, or other structural changes that theoretically cause discontinuities not captured in the explanatory variables. As such, they may improve explanatory power and goodness of fit and can be useful when investigating potential policy impacts. Dummy variables are also helpful in implementing fixed effects to explore regional differences (e.g., D. Greene (1981)) when using panel data, as described in Section 2.2.3. They are similarly used to account for periodical (e.g., seasonal) differences. In general, the use of a dummy variable for these applications should be implemented based on theoretical considerations. Table 12 provides a list of dummy variables found in some of the key literature.

Table 12: Selection of fixed effects and other dummy variables used in the literature

Source	Variables (separated by comma)
(Kwast 1980)	Oil crisis, regional
(D. Greene, State-Level Stock-System Model of Gasoline Demand 1981)	Regional (price and income)
(McRae 1994)	Regional (by country, 11 Asian countries)
(Hausman and Newey 1995)	Regional (20 U.S. regions)
(Schimek 1996)	Gas rationing (1974 and 1979)
(HDR/HLB 2007)	Tax-related (change in gasoline consumption measurement)
(WA DOT 2010)	For severe shortages
(Burke and Nishitateno 2013)	Year
(Wachs and Heimsath 2015)	OR State ethanol blending mandate (2008)

5.3 Alternative Econometric Approaches

5.3.1 Non-parametric and semi-parametric forms

Non-parametric and semi-parametric functional forms are much more flexible than the traditional log-linear, or even trans-log, approaches. The coefficients of each explanatory variable can be non-parametric functions (with no prescribed functional form) of a set of attribute variables, which could be determined by geography (e.g., state characteristics) or other factors.[45] The relevant literature uses these models to address some of the heterogeneity in elasticities. For example, urban residents may respond differently to changes in price or income than rural residents would. These models, which are more graphical in nature, can help researchers more accurately specify parametric models as well. Three of the earliest non- and semi-parametric models are briefly discussed below along with a more recent effort.

In the earliest analysis of nonparametric gasoline consumption regression models in the literature review, Hausman and Newey (1995) address the general lack of knowledge regarding parametric form of demand functions (e.g., gasoline). They suggest this lack of knowledge often leads to model mis-specification. Three different approaches are compared: kernel, cubic regression spline, and power series. Compared to a parallel analysis using two traditional parametric forms (log-linear and trans-log), the non-parametric model estimates have much more complex shapes. This indicates a potential need for more flexible functional forms.

Schmalensee and Stoker (1999) use a semi-parametric approach to determine how income elasticity responds to changes in income, while also addressing the lack of gasoline consumption modeling using household-level data. The graphical output of the semi-parametric approach is used to help specify the optimal functional form. Yatchew and No (2001) build on the previous two models and develop a more comprehensive semi-parametric model that incorporate both price and demographics.

Liu (2014) briefly reviews past literature on semi-parametric gasoline consumption modeling, then uses a semi-parametric model to estimate quarterly U.S. gasoline demand at the state level. She compares a semi-parametric model to both log-linear and trans-log functional forms, and finds that the former tends to give relatively smaller gasoline demand elasticity values. This is likely due to the increased number of sources of heterogeneity (i.e. not only price and income, but also state attributes and time).

Additional models that use or assess non- and semi-parametric modeling processes that were not reviewed due to schedule constraints, include: Pace (1998), Wadud, Noland and Graham (2010), Blundell, Horowitz and Parey (2012), and Blundell, Horowitz and Parey (2016).

5.3.2 Cointegration Techniques

Some authors assert that the time series data used in gasoline consumption estimation are non-stationary, meaning that their statistical properties (e.g., mean, variance, autocorrelation) are not constant over time (Wasserfallen and Güntensperger 1988). For example, periodic fluctuations in data (e.g., seasonality) imply that it is non-stationary. Most statistical methods are based on the assumption

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[45] Examples of how the non- and semi-parametric coefficients can be estimated are found in Cai and Li (2008) and Hausman and Newey (1995).

of stationarity since statistical properties, and hence the model coefficients, otherwise depend on the sample size and/or the time period over which the sample is drawn. In addition, regressions using non-stationary correlated data can result in estimation of an entirely spurious relationship.[46] This is an important consideration for both time-series (e.g., ARIMA – see Section 5.4.1) and econometric regression models. Two common methods to check for non-stationarity are to examine the autocorrelation function (ACF) plot and/or apply the Augmented Dickey-Fuller test (a type of unit-root test). Researchers often use first differencing to "stationarize" the data (e.g., the annual model in WA DOT (2010)). First differencing simply uses the change in each variable (for all variables) between the current and prior time period ($X_t – X_{t-1}$), rather than the current value (X_t) of the variable.

Basso and Oum (2007) identify first differencing as the "classical approach" to dealing with non-stationarity. The level of differencing required to stationarize data is denoted as its *order of integration*; for example, a time series that has been differenced once (one observation to the next) has undergone an *I(1)* process. Seasonal differencing is similar, but is applied from one *year* to the next rather than one observation period (e.g., monthly). Autoregressive time-series models (e.g. AR or MA) require stationary data and, therefore, differencing is a valuable tool (leading to an ARIMA). However, taking the same approach on a regression model eliminates its ability to predict relationships between the levels of variables. As a result, the model is no longer capable of predicting long-run relationships and other approaches are preferred.

In many cases, two or more variables can be *I(1)* while certain combinations of the variables can be stationary. This is called cointegration, and generally implies that the variables "obey an equilibrium relationship in the long run" (Basso and Oum 2007). An error correction model (ECM) can be used to correct these variables in the short-run, based on their long-run equilibrium tendency. A great deal of literature is available on cointegration and the techniques involved, with the most concise and complete (based on citation in other publications) being Hendry and Juselius (2000) and Maddala and Kim (1999), respectively. The literature review includes five gasoline consumption models that have implemented cointegration and/or ECM techniques: Bentzen (1994), Eltony and Al-Mutairi (1995), Samimi (1995), Ramanathan (1999), Dahl and Kurtubi (2001), and Dossary and Dahl (2009). They all use aggregated data in reduced-form econometric regression models and are primarily non-U.S. based.

One potentially important result is found when cointegration techniques are applied to static models (no-lags) using time series data, an approach which has been discarded in the recent past due to the biases discussed in Section 2.2.2. Such a model, if the variables are co-integrated, would predict the structural long-run relationship. Considering static models' inherent tendency to under-predict price elasticity, Basso and Oum (2007) roughly estimate that the long-run price elasticities provided by dynamic values could be over-estimated by 25-30%. A more recent study, Dahl (2012), indicates that cointegration is an important area for further research, since it does not have a wide base of historical usage

[46] Spurious correlation refers to the situation when two non-stationary but independent variables appear to be correlated when there is no causal mechanism between them. They may or may not both be causally related to another variable.

5.3.3 Other considerations

Lagging techniques/approaches

Static models - those that use either unlagged time series data or cross-sectional data - assume that observed demand is in equilibrium with the independent variable under observation (e.g., price, income) (Wadud 2007). Recognizing that a lagged response exists, many models incorporate lagged endogenous and exogenous variables to better explain variation in gasoline consumption. There are several approaches to lagging; this paper is not intended to offer extended discussion on each but provides references for further review.

Two of the most commonly cited lagging approaches are Koyck (also known as geometric), which lags the endogenous variable, and distributed (also known as polynomial) which lags exogenous variables. The latter requires more data, but is preferred because it only uses exogenous explanatory variables. After studying estimates from multiple different lagging approaches used with household-level data, Hill (1986) determined that a Koyck model is not supported by data on annual miles driven, and that “the Koyck model is soundly rejected in favor of a dynamic which requires at least two periods before price and income effects settle into such a pattern.” Baltagi and Griffin (1983) and Drollas (1984) also conducted similar studies to determine proper lagging structure for gasoline consumption.

Dahl, in a study of many models incorporating lag, concluded that price lags appear to be longer than income lags; longer lags may be appropriate in general; and that lagging an endogenous variable less than a year is likely not appropriate. Additionally, she concludes that, without annual lags, models based on monthly and quarterly data will only reflect short-run adjustments (Dahl 1986). In a later paper, she emphasizes the inherent difficulty in estimating the optimal lag structure for lagged endogenous models (Dahl and Sterner 1991).

Error components

Error components of models compensate for aggregation problems (e.g., pooling panel data), systematic residuals due to autocorrelation and heteroscedasticity, or other variations that cannot be predicted with the usual independent variable set (Blum, Foos and Gaudry 1988). As discussed in Section 5.3.2, cointegration techniques and the ECM approach have been used to identify and correct error due to non-stationarity.

A number of other studies have been conducted to reduce pooling errors (Balestra and Nerlove 1966; Houthakker, Verleger and Sheehan 1974; Mehta, Narasimham and Swamy 1978; Berzeg 1982), but an in-depth review was beyond the scope of this report.

5.4 Alternative Modeling Approaches

This section provides an overview of common modeling approaches found in the literature which depart from the structural approach found in the STEO model.

5.4.1 Time series (non-explanatory) models

Time series, or autoregression, models forecast future values of a dependent variables based on combinations of its past values. The independent variables used are usually either the actual past values of the dependent variable (characterized using AR(*p*), where *p* indicates the number of lagged values of the dependent variable used as predictors), or a moving average of past forecast errors of the dependent variable (characterized using MA(*q*), where *q* indicates the number of past forecast errors used as predictors). The most common time-series model used in the literature was a combination of these two, called an auto-regressive integrated moving average (ARIMA) model. This is characterized using ARIMA(*p*,*d*,*q*), where the new variable *d* indicates the degree of differencing involved.

Time-series gasoline consumption models are commonly used in state governments' fuel tax revenue (based on gasoline consumption) forecasting efforts,[47] a trend supported by a recent National Academy of Sciences review of state revenue forecasting models which found: "mathematically sophisticated models were not shown to be more accurate than simple projections of expert opinions; or considered to be worth the added procedural burden and data requirements" (Wachs and Heimsath 2015). This is the conclusion, even though they note that most states use an econometric model to forecast revenue. Table 13 below identifies the time-series/autoregression models identified in the literature review. It should be noted that this is only a partial list; an exhaustive search for time-series analysis literature was not conducted.

Table 13: Examples of time-series/autoregression models identified in the literature

Model type	Notes	Source
AR(6) MA(1)	1-year forecast; Monthly; using 84 months data	(Cervero 1985)
AR(1) MA(3)	2-3 year short-term; Monthly; WA State model (regression used for long-term)	(Wachs and Heimsath 2015)

One interesting consideration is a combined regression and time series model. The regression would provide the appeal of economic theory, while the time series model would allow for updated forecasts as new information becomes available (for instance, in an annual regression with quarterly time-series analysis, when the error of a first quarter forecast is revealed, it can be used to update the subsequent three quarters). This is discussed by Myer and Yanagida (1984), although for alfalfa hay- not gasoline consumption.

5.4.2 Qualitative Approaches

Qualitative approaches are rare in the literature and are primarily used for state models. The most common published qualitative approach is called Risk Analysis Process (RAP). RAP was developed by HDR/HLB Decision Economics, Inc. to combine the benefits of scenario development and sensitivity analysis. It measures the probability that an outcome will materialize by constructing probability distributions for the forecasts of each explanatory variable. Each variable can then be adjusted independently within the distribution, and the probability of the final model output can be estimated. The RAP has four steps (directly quoted from the RAP primer in (HDR/HLB 2007):

1. *Defining the structure and logic of the forecasting problem;*
2. *Assigning estimates and ranges (probability distributions) to each variable and forecasting coefficient in the forecasting structure and logic;*
3. *Engaging experts and stakeholders in assessment of model and assumption risks (the "RAP Session"); and*
4. *Issuing forecast risk analysis.*

[47] Cervero (1985) recommends ARIMAs for this purpose, and develops examples for 3 states (CA, NY, and IA).

This process is explicitly used in two different state models, Arizona (Arizona DOT 2016) and Missouri (HDR/HLB 2007).

The only other qualitative approach identified in the review was by Good and Irwin (2016), who projected U.S. gasoline consumption qualitatively after analyzing historical (1990-2015) VMT and vehicle efficiency (mpg) trends. They specifically point out that they disagree with EIA's STEO projections for 2017 because they appear to assume no growth in VMT for the year.

5.4.3 Neural Networks

One of the more unique and recent approaches to gasoline consumption forecasting is the use of models based on an artificial neural network (ANN). ANN methods are based on mathematical models of the brain, and use complex non-linear relationships between the dependent and explanatory variables. They are data driven and do not apply a pre-existing economic or behavioral theory, but rather are designed to discover and utilize such theory as they operate. The process and methodology are not yet mature, since researchers are still investigating whether ANN models could provide better estimations than traditional linear regressions.

This approach was not specifically investigated or sought out in the literature search process, but might be an interesting topic for additional future work. A few models were identified in the literature: a hybrid ANN/ARIMA model of gasoline consumption (Jahromi and Gholami 2016); an ANN gasoline consumption model using time series price and car registration data as determinants (Nasr, Badr and Joun 2002); and a performance comparison between ANN and linear energy demand/consumption models (Darbellay and Slama 2000).

5.5 Data Disaggregation and Heterogeneous Elasticities

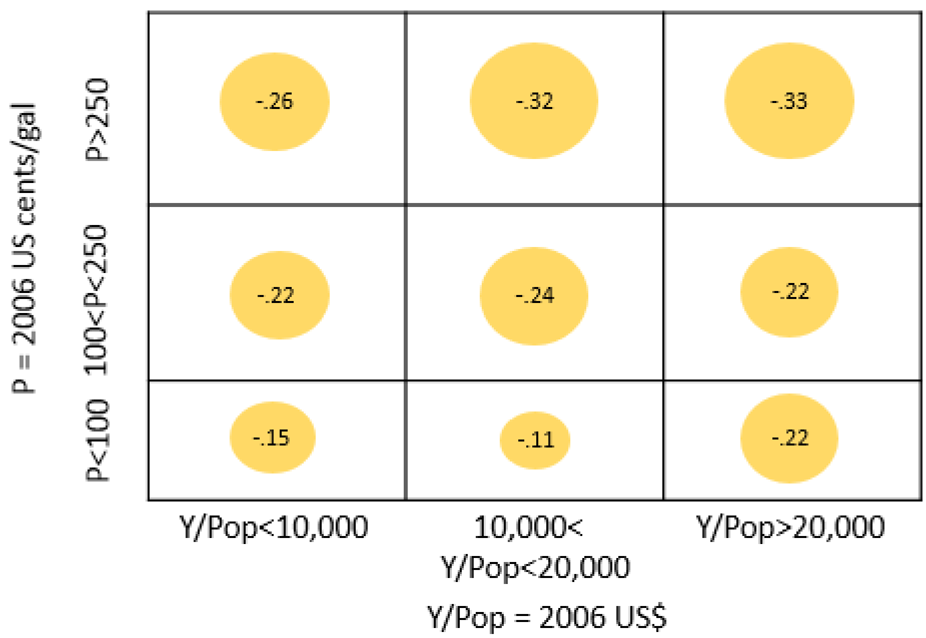
Use of aggregated national data neglects known heterogeneity and fundamentally assumes a constant distribution in underlying variables. This potentially fails to capture the impact of longer term structural change in demographic, economic, and other variables. Examples include increasing urbanization, the aging of the population, shifts in income distribution, and generational differences in driving behavior and mobility choices. Additional explanatory power may be found through disaggregating data in various dimensions.

Elasticity Heterogeneity

Most past literature on gasoline consumption modeling has focused on log-linear models using aggregate data (generally at the national or regional level), which assume constant elasticities. Schipper, et al. (1993) finds that studies using state or regional data typically produce similar estimates to those that use national data, although other empirical results indicate that gasoline demand and/or vehicle distance traveled varies significantly across and within populations (Gillingham and Munk-Nielsen 2016; Ke and McMullen 2016; Kayser 2000; Dargay and Goodwin 1995; McRae 1994; Dahl 1986; Drollas 1984). Older studies analyze (and disagree on) heterogeneity over time (Dahl 1982; Kouris 1983; Goodwin 1992). In general, data disaggregation by time, geography (down to the state, city, or household level), and/or various demographics has been suggested as a path to more precise elasticity estimates. Breaking the data down to the state or city level addresses some of the elasticity heterogeneity due to factors like weather, regulations, and driving conditions. Identifying temporal heterogeneity allows the model to adjust for, for example, the effects of dramatic gasoline price fluctuations on consumer driving behavior, or the steady increase in personal income over time. Demographic differences are generally assessed on a household-level basis, and offer far more explanation at the expense of higher data requirements. This section discusses both reduced-form and structural model literature that address these three approaches to disaggregation.

Two notable studies (Gallini 1983, Eltony 1993) both model gasoline consumption in Canada, with aggregate and disaggregate fuel efficiency information respectively. Aside from the fuel efficiency data disaggregation, the models are identical. The resulting price elasticity values are very similar (-0.312 and -0.364), but Eltony's results allocate much more explanatory importance to fuel efficiency. Eltony's results indicate that 75% of consumer response to gasoline price changes in the short-run can be attributed to vehicle distanced traveled, 15% to vehicle stock, and 10% to vehicle efficiency (versus Gallini's 4% allocation to vehicle efficiency).

Much of the literature regarding functional forms for disaggregated data centers on how to model the interaction between price and income. Research suggests that lower income households may respond less severely to price and income fluctuations because a large portion of their VMT is non-discretionary, whereas high income households could reduce unnecessary trips or purchase a new more fuel efficient vehicle. Goodwin, Dargay and Hanly (2004) present a mathematical argument that price elasticity is negatively related to income, although the exact relationship is still not fully understood. A larger meta-analysis of price and income elasticities by Dahl (2012) (including over 100 gasoline consumption models and studies), finds considerable price elasticity variation within price and income ranges, as summarized in Figure 3, and finds that income elasticities tend to be negatively related to income per capita.



Notes: Y = GDP; Pop = population; P = gasoline price
Size of the bubbles represent the magnitude of the elasticity

Figure 3: Gasoline price elasticities across price and income categories. From Dahl (2012)

Impact on Functional Forms

Several studies on the interaction between price and income elasticities have led researchers to use either trans-log or non/semi-parametric functional forms, fed by household-level survey data, to model gasoline consumption. Using a log-linear demand model, in which the elasticities are constant, may not be optimal for these relationships. For example, Archibald and Gillingham (1980) find that low income households are more responsive to changes in gasoline price and in income, while Hausman and Newey (1995) find that price elasticity is dependent on price but not on income. Kayser (2000) finds that "the interaction term between the price of gasoline and income implies that the income elasticity is lower when prices are higher, and that the price elasticity is greater at higher levels of income" (similarly identified by Wadud, Graham, and Noland (2010)), and suggests integrating price/income interaction and income squared terms as independent variables (a trans-log functional form).

Liu (2014) uses a semi-parametric model to determine the sources of heterogeneity among states and over time. The results of a simulated 10-cent gasoline tax increase range from a 2% decrease (Utah) down to a 0.1% decrease (New Jersey) in fuel consumption, with the biggest contributors to heterogeneity being urban form, average vehicle fuel efficiency, and state funding of public transit. Her analysis of the heterogeneity over time indicates a consistent increase in both price and income elasticity between 1994 and 2008 due to a series of economic changes (e.g., fluctuations in gasoline price, growth of personal income, and macroeconomic changes).

Table 14 below compiles explanatory variables that use disaggregate data in the literature. More discussion is available in the sources cited.

Table 14: Disaggregated explanatory variables used in the literature (not including household-level disaggregation)

Explanatory variable	Disaggregated by	Source
State funding of public transit	State	(Liu 2014)
Percentage of trucks	State	(Liu 2014)
Vehicle stock	State (cars and trucks)	(D. Greene, State-Level Stock-System Model of Gasoline Demand 1981)
	Country (cars)	(McRae 1994)
Population density	State	(Liu 2014; D. Greene 1981; Schimek 1996)[48]
Unemployment rate	State	(Liu 2014)
Employment rate	State	(D. Greene, State-Level Stock-System Model of Gasoline Demand 1981)
Year	State	(Liu 2014)
Gasoline prices	State	(Liu 2014; D. Greene 1981; Schimek 1996)
	Country	(McRae 1994)
Personal income per capita	State	(Liu 2014; D. Green 1981)
	Country (GDP per capita)	(McRae 1994)
Median household income	State	(Schimek 1996)

[48] Also tested *share of a state population living in metropolitan areas* as an alternative proxy for urbanization.

Regional price and income dummies	State	(D. Greene, State-Level Stock-System Model of Gasoline Demand 1981)

One of the above studies, Schimek (1996), concludes that the state-level data produces inconclusive results and the authors suggest that this may be attributable to U.S. CAFE standards.

Household-level Data

Disaggregating down to the household level allows a model to estimate the effects of some potentially key, changing, demographic determinants of automobile fuel consumption, like the age of household members, number of drivers per household, household income, and number of children. Household-level decisions regarding daily activities like work, school, entertainment, shopping, etc. are drivers of the total need to travel, from which gasoline demand is primarily derived. An analysis with this level of granularity can potentially identify even more of the heterogeneity in price and income elasticities (compared to State or city level disaggregation), for instance identifying whether high income households respond differently to variations in gasoline price.[49] Similarly, using average age of household may account for the effects of an aging population. Such shifts may not be significantly large over the forecast period of a short-term model, but may be important in subsequent applications of the model over time. For example, model parameters may be estimated in 2017 using historical data yet still be valid in future years despite changes in demographics because of the explicit use of disaggregated data and explanatory variables. Table 15 below identifies some of the different demographic variables used by a number of models based on household-level data.

Table 15: Sampling of household-level variable types from the literature[50]

Explanatory variable	Models using the variable[51]
Household income	(Gillingham and Munk-Nielsen 2016; Ke and McMullen 2016; Yatchew and No 2001; Kayser 2000; Puller and Greening 1999; Schmalensee and Stoker 1999; Hausman and Newey 1995; Eltony 1993; Lin, Botsas and Monroe 1985)
Household income, squared	(Kayser 2000)
Unemployment rate	(Eltony 1993)
Deflated total expenditure	(Wadud, Graham and Noland 2010; Archibald and Gillingham 1981; Archibald and Gillingham 1980)
Deflated total expenditure, squared	(Archibald and Gillingham 1981), (Archibald and Gillingham 1980)
Expenditure/Urbanization interaction	(Wadud, Graham and Noland 2010)
Man-days lost in the car industry due to strikes	(Eltony 1993)

[49] This might indicate that gasoline consumption would track with GDP per capita.

[50] Additional notes on the impacts of changes in these variables can be found in Dahl (1986). Gillingham and Munk-Nielsen (2016) and Ke and McMullen (2016) reference models for VMT, not gasoline consumption.

[51] Paul and Greening (1999) used the variables in both one- and two-equation models.

Relative price of gasoline	(Archibald and Gillingham 1981; Archibald and Gillingham 1980)
Relative price of gasoline, squared	(Archibald and Gillingham 1981; Archibald and Gillingham 1980)
Price of gasoline	(Kayser 2000; Puller and Greening 1999;[52] Hausman and Newey 1995; Eltony 1993;[52] Archibald and Gillingham 1981)
Price of gasoline per mile	(Ke and McMullen 2016; Eltony 1993; Lin, Botsas and Monroe 1985)
Price/Income interaction	(Kayser 2000)
Price/total expenditure interaction	(Archibald and Gillingham 1981)
Price/urbanization interaction	(Wadud, Graham and Noland 2010)
Employment status of head of household	(Kayser 2000)
Weeks of employment of head and wife	(Puller and Greening 1999; Hill 1986)
Rural or urban, urbanization, population density (dummy or explanatory)	(Gillingham and Munk-Nielsen 2016; Ke and McMullen 2016; Wadud, Graham and Noland 2010; Yatchew and No 2001; Kayser 2000; Puller and Greening 1999; Schmalensee and Stoker 1999; Lin, Botsas and Monroe 1985; Archibald and Gillingham 1980; Archibald and Gillingham 1981)
Geographic Region (dummy or explanatory)	(Ke and McMullen 2016; Wadud, Graham and Noland 2010; Schmalensee and Stoker 1999; Eltony 1993; Archibald and Gillingham 1980; Archibald and Gillingham 1981)
Number of warm days	(Lin, Botsas and Monroe 1985)
Public transportation availability	(Gillingham and Munk-Nielsen 2016; Kayser 2000)
Access to company car	(Gillingham and Munk-Nielsen 2016)
Distance to work	(Gillingham and Munk-Nielsen 2016)
Number of visits by out-of-state automobiles	(Lin, Botsas and Monroe 1985)
Percentage of employment using non-auto transport means to work	(Lin, Botsas and Monroe 1985)
Household size	(Wadud, Graham and Noland 2010; Yatchew and No 2001; Schmalensee and Stoker 1999)
Number of drivers	(Yatchew and No 2001; Schmalensee and Stoker 1999; Lin, Botsas and Monroe 1985) [53]
Household members of driving age	(Eltony 1993; Hill 1986)
Total family size/number of persons in household	(Ke and McMullen 2016; Hill 1986)
Number of children (or persons less than 18 years old)	(Gillingham and Munk-Nielsen 2016; Ke and McMullen 2016; Wadud, Graham and Noland 2010; Kayser 2000; Puller and Greening 1999; Archibald and Gillingham 1981; Archibald and Gillingham 1980)

[52] Lagged 1, 2, 3, and 4 time periods

[53] Percentage of drivers age 18-44

Number of adults	(Yatchew and No 2001; Kayser 2000; Schmalensee and Stoker 1999; Archibald and Gillingham 1981; Archibald and Gillingham 1980)
Number of working adults or employment per household	(Puller and Greening 1999; Lin, Botsas and Monroe 1985; Archibald and Gillingham 1981; Archibald and Gillingham 1980)
Number of adults over 64 years old	(Wadud, Graham and Noland 2010)
Household includes retired adult	(Puller and Greening 1999)
Taste (demographic) differences[54]	(Ke and McMullen 2016; Wadud, Graham and Noland 2010; Kayser 2000; Puller and Greening 1999; Schmalensee and Stoker 1999; Yatchew and No 2001; Hill 1986; Archibald and Gillingham 1981; Archibald and Gillingham 1980)
Age squared of reference person	(Gillingham and Munk-Nielsen 2016; Ke and McMullen 2016; Puller and Greening 1999)
Number of cars	(Ke and McMullen 2016; Wadud, Graham and Noland 2010; Eltony 1993; Lin, Botsas and Monroe 1985; Archibald and Gillingham 1981; Archibald and Gillingham 1980)
Number of vehicles (not cars, SUVs, or vans)	(Wadud, Graham and Noland 2010)
Shares of buses and trucks	(Lin, Botsas and Monroe 1985)
Fuel efficiency	(Kayser 2000; Eltony 1993;[55] Lin, Botsas and Monroe 1985; Archibald and Gillingham 1981;[56] Archibald and Gillingham 1980)[56]
Lagged endogenous	(Wadud, Graham and Noland 2010; Hill 1986)
Lagged exogenous (all)	(Hill 1986)
Dummy: Does the household own a hybrid or electric vehicle?	(Ke and McMullen 2016)
Dummy: Does one household member use public transit for work/school?	(Ke and McMullen 2016)
Dummy: Did the household move?	(Hill 1986)
Dummy: Are they homeowners?	(Hill 1986)

Hill (1986) uses a particularly complex dynamic regression model with household-level data, including both a lagged endogenous explanatory variable as well as lags of every exogenous variable. In addition to the variable selection shown in the table above, he uses a subset of variables specifically to improve the instrument of the prior year's gasoline demand. These variables include: miles to work, number of cars, and a dummy variable indicating if there is public transportation within walking distance of the residence.

One of the biggest barriers to using disaggregated data in a gasoline consumption model is the unavailability of reliable data. Dargay and Goodwin (1995) suggest that, ideally, a model would use

[54] Includes a number of demographic variables (ethnicity, gender, age, marital status, educational attainment).
[55] Fuel efficiency is modeled using the size class of cars.
[56] Fuel efficiency is modeled using number of engine cylinders, based on older studies indicating high fuel efficiency dependency on number of cylinders.

large-sample panel surveys with repeated observations on the same set of individuals for many years. Such a dataset is non-existent, unfortunately, so researchers use the best data available. Table 16 below provides the data sources used for the models discussed in this section.

Table 16: Data sources used in disaggregated-data-based models, United States

Data Source	Model using this source
Consumer Expenditure Survey (U.S. Bureau of Labor Statistics)	(Archibald and Gillingham 1980; Archibald and Gillingham 1981; Puller and Greening 1999; West and Williams III 2004; Wadud, Graham and Noland 2010)
U.S. DOT/FHWA Highway Statistics	(Lin, Botsas, & Monroe, 1985) Income, car stock (Schimek 1996)
National Petroleum News Factbook	(Lin, Botsas and Monroe 1985)
U.S. DOC Survey of Current Business	(Lin, Botsas and Monroe 1985)
U.S. BOC Statistical Abstract of the U.S.	(Lin, Botsas and Monroe 1985)
U.S. DOC Climatological Data	(Lin, Botsas and Monroe 1985)
U.S. BOC Census of Population	(Lin, Botsas and Monroe 1985)
U.S. BOC National Travel Survey	(Lin, Botsas and Monroe 1985)
Polk data	(Lin, Botsas and Monroe 1985)
U.S. DOT National Household Travel Survey	(Blundell, Horowitz and Parey 2012)
Panel Study of Income Dynamics[57]	(Hill 1986)
Oil and Gas Journal	(Hill, 1986)
U.S. DOE Residential Energy Consumption Survey	Gasoline price and income (Hausman and Newey 1995)
U.S. EIA Residential Transportation Energy Consumption Survey	Gasoline price and income (Hausman and Newey 1995)
Statistical Abstract of the United States	Population density and share of state population in metropolitan areas (Schimek 1996)
EIA State Energy Demand Report	Gasoline prices (Schimek 1996)
R.L. Polk's National Vehicle Population Profile	Using data disaggregated down to the vehicle level (Gillingham 2014)
Oregon Household Activities Survey	(Ke and McMullen 2016)

Selected effects of demographic variables

In one of the earliest models to include demographic data, Archibald and Gillingham (1981) draw several key conclusions: degree of urbanization primarily affects single-car households, there is a level of regional heterogeneity of response to price and income changes, all characteristics of the head of household significantly affect gasoline consumption (also see Puller and Greening (1999)), and single- and multi-car households respond significantly different to both price and total expenditure changes.

Schmalensee and Stoker (1999) test a semi-parametric model (around 5000 observations) to guide specification of the parametric model. They find no evidence of variation in income elasticity of demand over changes in income (at odds with much of the literature (Dahl 2012)). Key household-level

[57] Does not include gasoline prices

determinants were found to be age of household head (>50 years old) and number of drivers in the household; the latter effect cut estimated income elasticity in half. Overall, they find that using aggregate data likely over predicts future growth. Unfortunately, price data was not available for their model, so it was not included.

Yatchew and No (2001) develop a semi-parametric model (6,230 observations) to modify the weaknesses in the previous two household-level data-based efforts (lack of demographic variables in Hausman and Newey (1995) and lack of price data in Schmalensee and Stoker (1999)). They find that price is "essentially orthogonal" to demographic variables and, therefore, omitting demographic variables will likely not lead to biased estimation of price elasticities (and vice versa). This would mean that neither Hausman and Newey's nor Schmalensee and Stoker's results are compromised. They also confirm Schmalensee and Stoker's finding that income elasticity estimates almost double when demographic effects are ignored. Additional findings include: urban families consume less gasoline than rural and the age of the driver significantly effects gasoline consumption (elasticity of 0.6).

In a more recent example, a reduced-form static household-level trans-log model by Wadud, Graham and Noland (2010), builds on past efforts by investigating the effects of demographic and location variables (specifically those that were determined in previous studies to have a significant impact on gasoline consumption) on price and income elasticities. A few of the findings, many of which are both confirmed and denied at varying levels in other studies, offer a sampling of the potential explanatory power provided by demographic variables: decreasing price and income elasticities with increasing income, lower gasoline consumption for female household heads and non-white household heads, lower gasoline consumption for households with higher education, and lower gasoline consumption for Southern and rural households.

Difficulties and considerations for disaggregate data

In addition to data availability, one potential difficulty in comparing models with different levels of geographic disaggregation is that many disaggregate models use household-level data, which only includes passenger car use, while models based on aggregate data may be picking up some of the commercial/industrial vehicle use. Additionally, aggregate studies generally follow dynamic specifications so that the short- and long-run elasticities are properly differentiated. Disaggregate studies tend to follow static specifications; the authors' judgement is required to define whether the results are short- or long-run. Most of the household-level data literature assumes a fixed car stock and demographic profile, thereby estimating short-run elasticities only.[58]

Aggregate data models implicitly capture the heterogeneous effects of demographic and economic variables, bypassing any explanation of the actual sources and causes of adjustment. Disaggregate data has the potential to provide this explanatory power, although it is harder to obtain and requires more flexible functional forms. Other gasoline consumption models based on disaggregate data that were not reviewed in-depth include: Berkowitz, et al. (1990) and West and Williams III (2004).

[58] See Puller and Greening (1999) for a long-run household-level data model.

6 Summary

This paper provides a partial review of the vast literature on modeling gasoline consumption. The literature search identified 169 documents, with some discovered up through the completion of this report. All of these documents are included in the attached bibliography. However, it was not possible to review all publications in depth and some were not reviewed at all due to their late discovery. As a result, this review is limited in the following ways:

- Scope – The primary focus of this review is highway gasoline consumption. The body of literature found for non-highway consumption was considerably smaller, though additional effort with a non-highway focus would likely find additional sources. Nearly all of the sources identified apply traditional modeling approaches. Therefore, many of the alternative modeling structures and approaches, such as non- and semi-parametric models or ANNs, were not investigated in sufficient detail to fully understand their potential contribution to the field.
- Depth - Documents not reviewed or only superficially reviewed might contain additional, valuable insights. Several recent publications that appear to be highly relevant were uncovered too late to be reviewed. It should also be noted that publications from one important resource, the Transportation Research Board, were not readily accessible.

After the initial literature search, the studies were prioritized to cover first those that contained literature or modeling reviews with goals similar to this study, and second, recent work that covers the breadth of the most promising possible additions to the approach used by EIA. The following publications were reviewed in more detail than the remaining sources and served as the starting point for the review:

- Basso, Leonardo, and Tae Hoon Oum. 2007. "Automobile Fuel Demand: A Critical Assessment of Empirical Methodologies."
- Dahl, Carol. 2012. "Measuring Global Gasoline and Diesel Price and Income Elasticities." *Energy Policy.*
- Goodwin, Phil, Joyce Dargay, and Mark Hanly. 2004. "Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review." *Transport Reviews.*
- Graham, Daniel, and Stephen Glaister. 2002. "The Demand for Automobile Fuel: A Survey of Elasticities." *Journal of Transport Economics and Policy.*
- Wadud, Zia. 2007. "Personal Tradable Carbon Permits for Road Transport: Heterogeneity of Demand Responses and Distributional Analysis." *ResearchGate.*

6.1 Key Findings

Key Determinants of Gasoline Consumption

The literature identifies several key determinants of gasoline consumption that operate both directly and indirectly (by influencing demand for travel and vehicles). These variables are listed below along with the measurements and definitions most commonly utilized in the literature reviewed. This list, as well as others included in Section 5.2, provide some alternative measures and variables for consideration in the STEO model.

- Income, including both real and nominal; national (GDP) and personal; aggregate and disaggregate (e.g., per household)
- Price of gasoline, including producer and consumer prices; real and nominal; relative and actual
- Car stock or ownership rates, primarily per capita or per household
- Employment, including both unemployment and employment rates; non-agricultural and overall labor force participation; aggregate and disaggregate (e.g., per household)
- Urban density, urbanization, and population density
- Lagged endogenous (gasoline consumption), typically lagged by one time step
- Lagged exogenous (income and gasoline price), typically lagged by one time step, but several alternative lag structures were presented (e.g., polynomial)

Best Practices

The most common model structure in the literature uses an econometric regression approach with reduced form dynamic specification, utilizing aggregated time-series data in a log-linear functional form. This structure can explain a great deal of the variation in gasoline consumption (primarily through price and income), while holding data requirements to a minimum (as opposed to disaggregated data, or the use of panel data).

Log-linear functional forms were used in earlier models based on statistical testing (goodness of fit or hypothesis testing) and continue to be popular, but trans-log forms are becoming more prevalent, especially in models using disaggregate household-level data. Trans-log specification allows the elasticities to vary across the range of explanatory variable and imposes no restrictions on the shape of the relationship. This flexibility is particularly useful for models that explicitly consider a wider range of heterogeneity (e.g., those based on disaggregated data).

There are many problems inherent to time-series analysis, a prominent issue being non-stationary data. Identifying and addressing non-stationarity, the former through common tests (e.g., Augmented Dickey-Fuller) and the latter using error correction models or co-integration, are both essential for an accurate econometric modeling. Some examples of gasoline consumption models using this process include: Bentzen (1994), Eltony and Al-Mutairi (1995), Samimi (1995), Ramanathan (1999), Dahl and Kurtubi (2001), and Dossary and Dahl (2009). Co-integration does not have a wide base of historical usage and is an important area for future research (Dahl 2012). Further investigation of this topic is required to determine its implications for the STEO model.

Lagged consumer response constitutes another important issue in time-series analysis, especially for higher resolution data (i.e., monthly versus annual data). As discussed in Section 5.3.3, adjustment to gasoline consumption may not occur simultaneously with changes in explanatory variables (e.g., price, income). This lagged response can be captured by a model with lagged endogenous and exogenous variables. Selecting the best lag structure is difficult, but Dahl (1986) notes that without annual lags, models based on monthly and quarterly data will only reflect short-run adjustments.

6.2 Promising Model Changes

Inclusion of Additional Determinants

EIA STEO does not include income as an explanatory variable, but nearly all the models identified and reviewed in the literature do. Measures found in the literature include both real and nominal, national (GDP) and personal, and aggregate and disaggregate (e.g., per household) income and consumer expenditures. Researchers have found it to be a statistically significantly explanatory variable for both gasoline consumption and VMT, in both short- and long-term analysis. Real personal disposable income and/or GDP data[59] indicate clear trends, variability, and response to specific events (e.g., the 2008 recession) and could add explanatory power.

Outside of income, the most frequently cited variable not currently used in EIA's STEO gasoline consumption module is urban density (urban form, population density, urbanization, and metropolitanization). The clear majority of models that include urban density find it to be statistically significant in estimating gasoline consumption. The path of this determinacy (i.e., how urban density effects fuel consumption) is not explicitly investigated in this report, although the literature suggests several theories.

Weather (average heating-degree-days) is the only independent variable used by EIA that is *not* included in several of the reviewed sources; only one household-level study uses it (Lin, Botsas and Monroe 1985).

Disaggregation

The current STEO gasoline consumption model does not use data disaggregated to the household- or state level. There is a large body of literature supporting the use of disaggregate data based on the consensus that elasticities (particularly price and income elasticities of gasoline consumption) are geographically, temporally, and demographically heterogeneous. Models using this type of data identify the specific sources of heterogeneity in price and income elasticities. For example, Schmalensee and Stoker (1999) find that utilizing a *number of drivers in household* variable cuts the income elasticity in half. Other behavioral determinants in addition to the key determinants listed in Section 6.1 include: habits, culture, taste, and household situation. In models using aggregate data, the effect of these factors are usually assumed to be implicitly explained (through price, income, or car stock). However, recent studies support the explanatory power of using disaggregate data to explicitly account for these determinants, where they are measureable. Such models offer the potential to explore why consumers purchase specific vehicles, why they drive the miles they do, and how trends in underlying features may impact projections of these dependent variables. The biggest limitation for disaggregation is data availability. However, new data collected by transportation network companies (e.g. Uber), crowd sourced applications, and other internet-connected devices could create large disaggregated datasets that enable successful implementation of these approaches.

The two most prominent directions for disaggregation found in the literature are geographic resolution and use of household level data. There was a consensus in the literature that urban density is a significant determinant of gasoline consumption, and the impact of this factor could be explored through geographic disaggregation. Puller and Greening (1999) employ a 2-component structural model like the STEO model but using household-level data. Additional review of relevant research is

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[59] See FRED U.S. economic data, U.S. Bureau of Economic Analysis, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/GDPC1 (accessed July 12, 2017).

recommended, starting with the economic theory behind household-level data (Becker 1965; Lancaster 1966). See Wadud, Graham, and Noland (2010) for more recent implementation and additional references. Should EIA decide to explore use of household or other disaggregate data, it might be important to investigate panel data analysis techniques and approaches.

6.3 Topics for Further Review

As discussed, this report represents a partial review of the vast literature relevant to short term gasoline consumption modeling. This study focused primarily on papers directly addressing highway consumption. Valuable insights could be found in additional literature addressing related econometric topics (e.g. VMT and non-highway consumption) and general techniques. Therefore, a more extensive review of the papers included in the complete bibliography and additional sources could expand the findings presented here. A partial list of specific topics not explored in this report that are worthy of further study includes:

- Investigate the potential to explicitly model non/off-highway demand. This market likely has different price and income elasticity, geographic variation, and response to urbanization. The U.S. FHWA maintains a series of off-highway motor fuel consumption models that cover recreational boating, agriculture, industrial/commercial, construction, and other non-highway recreational vehicles. The most recent update, U.S. Federal Highway Administration (2014), includes both methodological and data source updates.

- Explore the possibility of implementing asymmetric price elasticities. Dahl (2012) reviews prominent literature on the subject and notes that there is not a consensus on the impact of the symmetric price elasticity assumption. However, she suggests that it likely leads to over-estimates of the actual gasoline consumption response to price changes. The literature review completed for this report did not identify any further research on the topic.

- Further investigation of formal incorporation of technical progress and other factors rather than a general time trend variable.

- Exploration of techniques that utilize an instrumental variable (IV) specification to address endogeneity between gasoline price and demand. For examples, see Hughes et al. (2008), (Li, Linn and Muehlegger (2014), and Coglianese et al. (2015).

- Further exploration of studies applying multivariate time-series/autoregression techniques (structural vector autoregression), which are less data intensive than a structural model but offer more accuracy than a univariate time-series model. Although EIA workshop participants recommended against using a pure ARIMA, combining ARIMA and explanatory modeling could be valuable. This review did not identify a significant body of literature applying such techniques to gasoline consumption modeling, though Myer and Yanagida (1984) discuss this approach for an agricultural application.

- Investigate non- and semi-parametric models, as well as ANNs. Although these approaches have high data demands, they have proved highly valuable in a range of other applications and could be a worthwhile topic for further investigation.

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