



Fuel price elasticities in the U.S. combination trucking sector



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ABSTRACT

This paper estimates fuel price elasticities of combination trucking operations in the United States between 1970 and 2012. We evaluate trucking operations in terms of vehicle miles traveled and fuel consumption for combination trucks. Our explanatory variables include measures of economic activity, energy prices, and indicator variables that account for important regulatory shifts and changes in data collection and reporting in national transportation datasets. Our results suggest that fuel price elasticities in the United States' trucking sector have shifted from an elastic environment in the 1970s to a relatively inelastic environment today. We discuss the importance of these results for policymakers in light of new policies that aim to limit energy consumption and reduce greenhouse gas emissions from heavy-duty vehicles.

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Introduction

Heavy duty vehicles (HDVs) comprise an increasing share of vehicle miles traveled (VMT) and highway energy consumption in the United States (US). Although the portion of highway HDV VMT has increased modestly from 6% in 1970 to 9% in 2011 (BTS, 2014a), the share of highway HDV energy consumption has increased from 13% to 25% during the same time period (BTS, 2014b, 2014c, 2014d, 2014e). These trends have enhanced the relative importance of HDVs in national energy and emissions reduction strategies.

In 2011, the US embarked on an unprecedented regulatory program that establishes greenhouse gas (GHG) and fuel efficiency standards for the US trucking sector. These regulations were promulgated jointly through the US Environmental Protection Agency (EPA) and the US National Highway Transportation and Safety Administration (NHTSA) (EPA and NHTSA, 2011). EPA has responsibility for regulating GHG emissions from trucks (e.g., gCO₂/ton-mile), and NHTSA has responsibility for regulating fuel consumption (in gallons/1000 ton-mile). The standards, which affect trucks produced between model years 2014 and 2018, are expected to reduce fuel use by ~20% for combination trucks and ~10% for vocational trucks over the vehicle's lifetime (The White House, 2014a). In 2014 the US announced its plans to extend these regulations beyond model year 2018 (The White House, 2014b).

Yet, expectations about fuel savings from fuel efficiency standards may need to be tempered. By improving vehicle efficiencies, these types of regulations also have the effect of reducing fuel costs for trucking firms as measured in \$/mile or

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\$/ton-mile. These reduced fuel costs may induce increased activity or demand for the HDV services that essentially “give back” some of the intended energy savings.¹ This phenomenon has been labeled the “rebound effect” in the energy policy literature (Berkhout et al., 2000; De Borger and Mulalic, 2012; Greene, 2012; Greene et al., 1999; Greening et al., 2000; Matos and Silva, 2011; Small and Van Dender, 2005; Sorrell and Dimitropoulos, 2007; Winebrake et al., 2012).

For a variety of reasons discussed in previous work (Winebrake et al., 2012), there is no widely accepted estimate of the rebound effect from HDV efficiency standards. Additionally, robust time-series data on HDV fuel efficiency is lacking, as discussed in the concluding section of this paper. As an alternative, one can look to other elasticities – such as fuel price elasticities of truck activity – as proxies for the rebound effect under certain assumptions, including the assumption that firms respond to price increases and decreases symmetrically; that firms respond to changes in fuel prices and fuel efficiency uniformly; and that fuel efficiency itself is not affected by fuel price (Winebrake et al., 2012). However, there is some suggestive evidence in the literature that these assumptions may not hold (e.g. Dargay and Gately, 1997; Gately, 1993; Greene, 2012; Hymel and Small, 2015; Sentenac-Chemin, 2012; Winebrake et al., 2012).

This paper estimates fuel price elasticities of combination truck travel activity (measured in VMT) and diesel fuel demanded for the period 1970–2012. The results may be used as a rebound effect proxy under certain assumptions, as discussed above; however, more generally the results can help inform analyses that evaluate the impact of energy pricing on truck energy use, emissions, vehicle travel, and congestion, among others (Dahl, 2012; Graham and Glaister, 2004).

The paper is divided into six sections. Our ‘Background’ section provides context and background on fuel price elasticities of VMT demand and HDV demand elasticities with respect to energy costs. Next, a ‘Data and methodology’ section presents the modeling approach we used to evaluate our data. Sections ‘Results’ and ‘Discussion’ present our results and discuss these results, respectively. Lastly, the ‘Conclusion’ section places our results in context with new regulatory actions that exist now or are likely to occur in the near future.

Background

Most literature related to fuel consumption and vehicle travel demand elasticities focuses on gasoline and light duty vehicle (LDV) travel (Dahl, 2012; Espey, 1998; Graham and Glaister, 2004; Greene, 2012; Litman, 2013; Poor et al., 2007). To our knowledge, very little peer-reviewed literature examines fuel price elasticities of HDV travel activity or diesel fuel demand, perhaps because LDVs have been the target of regulations for decades and have tended to dominate highway VMT and energy use in the US (BTS, 2014a, 2014b).

Price elasticities of gasoline demand in the LDV sector tend to range between -0.30 and -0.10 . Elasticities of a smaller magnitude are found in the short term and with increasing incomes and lower relative gasoline prices (Brons et al., 2008; Dahl, 2012; Goodwin et al., 2004; Greene, 2012). Fuel price elasticities of LDV travel demand generate similar values; for example Goodwin et al. (2004) estimate a short-run price elasticity of VMT in the LDV sector of -0.10 , and a long run elasticity of -0.30 , and they note that these elasticities have declined in recent decades. Others have estimated the elasticity of vehicle travel with respect to gasoline prices in the US at approximately -0.24 , for the years 1968 to 2008 (Li et al., 2014). Recent research indicates that gasoline price elasticities declined in the later decades of the twentieth century, but may be increasing in the twenty-first century (Greene, 2012; Litman, 2013). However, given the difference in structure of LDV and HDV sectors [e.g. individual, utility-seeking drivers and households versus profit- and production-maximizing firms (Berkhout et al., 2000)], we cannot apply LDV or gasoline elasticities to the HDV sector with any confidence.

With respect to the literature that directly addresses elasticities for HDVs, we can look at three categories of research. First is the literature on fuel price elasticities for diesel fuel demand (diesel representing approximately 88% of HDV energy use) (ORNL, 2013a). This body of literature is relatively scarce. However, results from studies in this area indicate in general that diesel price elasticities tend to be much smaller in magnitude compared to gasoline; Dahl (2012), for instance, reviewing global fuel price elasticity studies, reports a US price elasticity of demand for diesel at -0.07 , compared to -0.30 for gasoline.² These results for the US tend to be much different than for other countries. Dahl (2012) reports the median price elasticity of diesel demand for all countries at -0.16 ; Barla et al. (2014) estimated the price elasticity of road diesel in Canada to be -0.43 (short run) to -0.8 (long run); and Liu (2004) reported a range of diesel price elasticities in OECD countries that vary by an order of magnitude and range from negative to positive.

A second category of literature exists on the *freight price* elasticity of demand for freight services, as measured as the change in ton-miles or tons shipped in response to a change in freight rates (\$/ton-mile or \$/ton) (Abdelwahab, 1998; Friedlaender and Spady, 1980; Oum et al., 1990, 1992; Winston, 1981; Zhou and Dai, 2012). These freight price elasticities vary greatly by region, commodity, shipment type, distance, availability of alternative modes, and other variables—and given the variability across published studies, elasticities estimated for these highly specific circumstances cannot be applied to aggregate trucking freight activity with much confidence. Additionally, the use of *freight price* elasticities as a proxy for *fuel*

¹ This is the definition of “rebound effect” we use in this paper, which is a common description found in the literature. We note that there are different types of rebound effects discussed in the literature – e.g., direct, indirect, and economy-wide (Winebrake et al., 2012). The results of our paper are most relevant for estimating the direct HDV rebound effect.

² Dahl (2012) notes that this might suggest that price is not influential for diesel demand, or there is too much noise in the data to isolate and measure the influence of fuel price changes. Dahl (2012) also showed that low price, high income countries show the least price response with more elastic response at higher price levels.

price elasticities requires one to assume that fuel cost impacts are passed on to customers in the form of freight rates; because fuel costs are only one component of operating costs, any use of freight price elasticities to estimate fuel cost elasticities would need to be adjusted accordingly (Winebrake et al., 2012). Lastly, differences in structures of the freight and non-freight (i.e. vocational) trucking sectors may preclude us from using freight price elasticities in non-freight sectors with confidence.

Third, there is a small body of literature that examines the elasticity of US HDV activity in response to a change in fuel price (\$/gal) and fuel costs (\$/mile or \$/ton-mile). Here, the results vary. For example, Gately (1990) did not find any statistically significant relationship between fuel price and HDV VMT, although this result may be unreliable because the time series properties of the variables in the model may not have been adequately addressed. West et al. (2011), examining the determinants of demand for freight trucking, estimated the fuel price elasticity of demand (as measured in ton-miles) at -0.05 . (However, limitations in US ton-mile data quality make us wary about placing too much confidence in this value.)³

For peer-reviewed studies examining fuel cost or fuel price elasticities of HDV activity outside of the US, De Berger and Mulalic (2012) estimated fuel cost elasticity of vehicle-kilometers in Denmark at -0.004 (short run) to -0.007 (long run), and the fuel cost elasticity of ton-kilometers (ton-km) at -0.193 (short run and long run). Their study also estimated the fuel price elasticity of energy demand at -0.133 (short run) to -0.221 (long run). Finally, Matos and Silva (2011) estimated the elasticity of HDV road freight (ton-km) with respect to energy service price (\$/ton-km) in Portugal at -0.24 ; in the same demand function equation, however, the estimated elasticity of HDV road freight with respect to energy price (\$/barrel of oil) was positive (0.159).

In summary, we find an important gap in the literature with respect to fuel price elasticities of travel demand for the US HDV sector. The next section presents the data and methodology that we use in our attempt to fill some of this gap.

Data and methodology

Data

Data for this analysis covers the period 1970–2012 and are available in the Supplementary Information (SI). The data can be divided into three main categories: (1) HDV activity data; (2) macroeconomic data; and, (3) energy price data.

HDV activity data includes VMT and fuel consumption data for combination trucks defined as “all [Class 7/8] trucks designed to be used in combination with one or more trailers with a gross vehicle weight rating over 26,000 lbs.” (AFDC, 2014; ORNL, 2013c). Vehicle miles traveled (CVMT) are estimated by the US Department of Transportation (DOT) FHWA (FHWA, 2011, 2013), which reports annual aggregate miles traveled by vehicle type in Table VM-1 of their annual *Highway Statistics* report. Combination truck fuel consumption (CFC) in million gallons per year is obtained from Oak Ridge National Labs and FHWA (FHWA, 2011, 2013; ORNL, 2013c).

Beginning in 2007, the FHWA made changes to its fuel consumption and VMT methodology which renders pre-2007 fuel consumption and VMT data reported in Table VM-1 incompatible with 2007+ data. In personal communication, FHWA analysts expressed more confidence in the new methodology and data. Per our request, FHWA applied their new (2007+) methodology to recalculate VMT and fuel consumption estimates for 2000+ data, but felt that the methodology could not be appropriately applied pre-2000. Therefore, for 1970–1999 and 2007–2012 we use publically available HDV VMT and fuel consumption data, but for year 2000–2006 we use FHWA revised and (as of this writing) unpublished data which is available to readers in the SI. The trends of these data across time are observed in Fig. 1, which also clearly shows the effect of FHWA's methodology shift beginning in 2000 (an issue we address later through our model specification).

The macroeconomic data we considered included gross domestic product (GDP), GDP per capita (GDPC), and total US import and exports (INTT) (BEA, 2013; US Census Bureau, 2000, 2012, 2013, 2014). These macroeconomic variables have been shown in previous work to drive freight transportation activity (Brogan et al., 2013; De Berger and Mulalic, 2012; Eom et al., 2012; Gately, 1990; Matos and Silva, 2011; West et al., 2011).

Although GDP and GDPC have traditionally been used as explanatory macroeconomic variables in similar analyses, some researchers have found that international trade is a better determinant of trucking demand than GDP (West et al., 2011). We hypothesize that this may be true because international trade measures the movement of material goods, while GDP measures economic activity that includes both goods and services. In this paper, we use international trade as our primary macroeconomic variable, and also introduce a new variable to the literature: international trade less petroleum (INTP) which modifies INTT by subtracting the portion of trade due to petroleum imports and exports (EIA, 2014b). This modification removes possible interdependence between energy price variables and international trade statistics. Trends in these variables are shown in Fig. 2.

³ The Bureau of Transportation Statistics (BTS) reports ton-mile data for “freight trucks” in Tables 1–50 of the National Transportation Statistics. However, these data exclude major portions of the freight sector including household, retail, service, and government shipments (including US mail), as discussed in BTS's 2004 report “Improvements in BTS Estimation of Ton-Miles”: www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/bts_working_papers/2004/paper_02/pdf/entire.pdf. The underestimation of ton-miles becomes obvious when BTS data are compared with the FHWA Freight Analysis Framework (FAF) for overlapping years. Further, ton-miles estimates for post-2007 are not comparable with earlier estimates due to FHWA methodology changes that impacted how VMT, which BTS uses to extrapolate ton-mile estimates in years where data are unavailable, is distributed among vehicle classes.

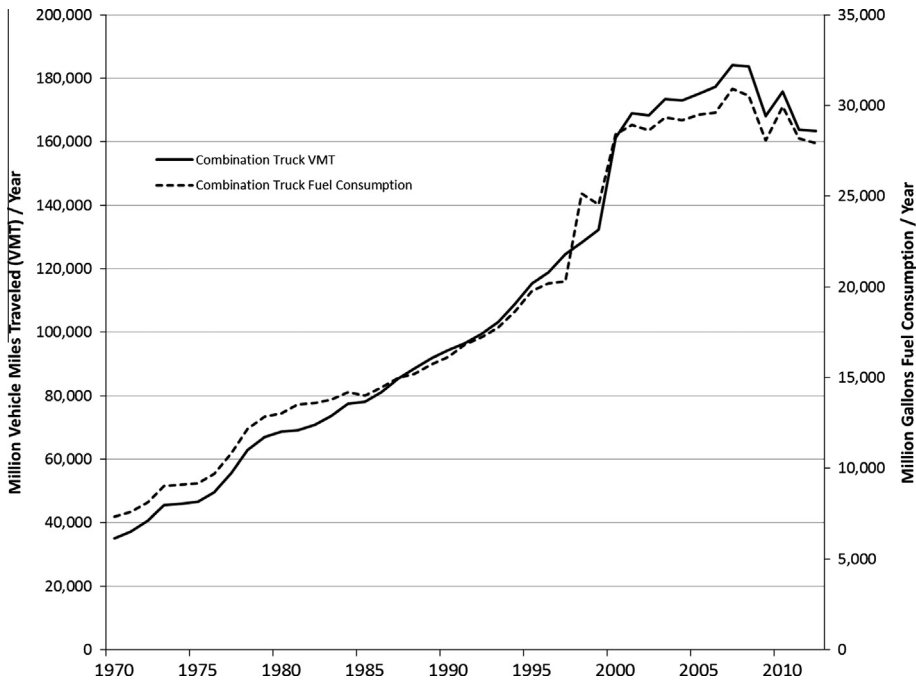


Fig. 1. Vehicle miles traveled and fuel consumption by US combination trucks (1970–2012) showing trends over time and impacts associated with data collection and reporting methodologies in the year 2000.

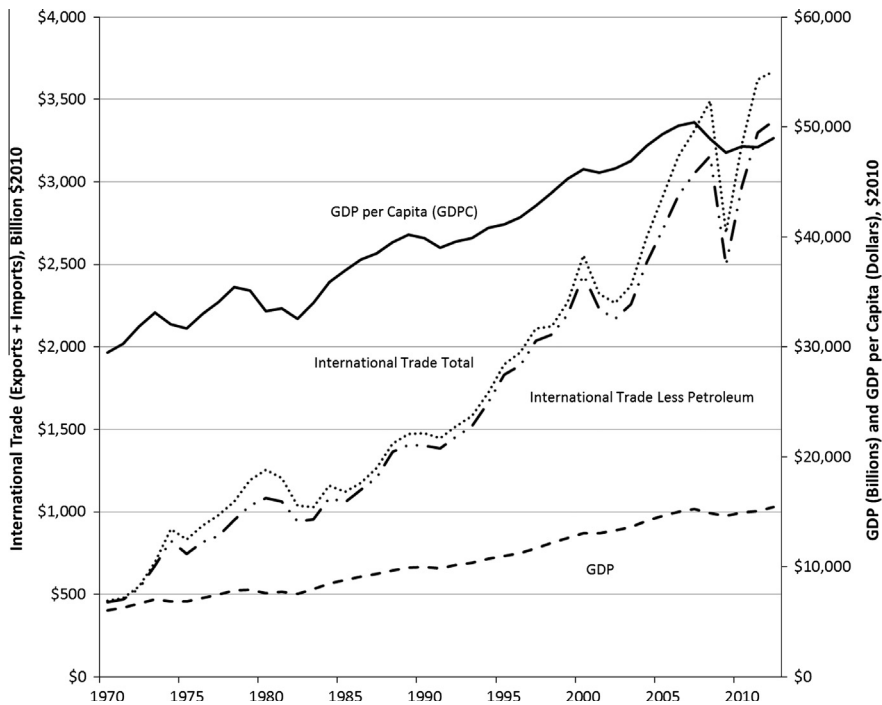


Fig. 2. US real GDP, GDP per capita, international trade (value of exports and imports, total) and international trade less petroleum for 1970–2012 in 2010\$.

Energy price data are represented by US highway diesel fuel prices (*DPRI*) in 2010\$/gallon. Fuel price data for the years 1980–2012 are obtained from the U.S. DOE Energy Information Administration (EIA, 2014c; ORNL, 2013d). Because highway diesel fuel price data are unavailable prior to 1980, we derived diesel prices for 1970–1979 using the change in gasoline

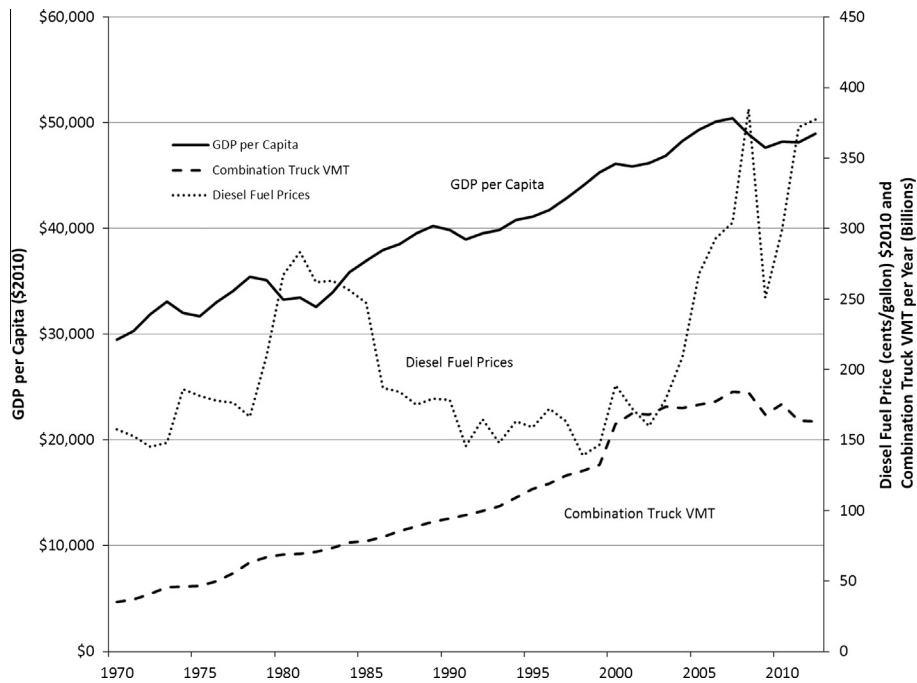


Fig. 3. Combination truck VMT, GDP per capita, and real diesel fuel prices (cents/gallon, \$2010) for 1970–2012.

prices during that time as a guide – an approach discussed in the SI.⁴ Fig. 3 depicts real prices for diesel fuel over time, along with VMT data for combination trucks and GDP per capita in \$2010.

Model specification

There are a variety of analytical models used in the literature for studying demand elasticities. These models are well summarized in Ajanovic et al. (2012), which presents econometric equations of energy demand (E_t) based on price (P_t), income (Y_t), and a lagged demand (E_{t-1}), or:

$$E_t = f(P_t, Y_t, E_{t-1})$$

Ajanovic et al. (2012) identifies a series of nine types of models that can emerge from this basic formulation, covering both short-term and long-term effects, and with possible inclusion of additional independent variables. Using natural log transformations, a dynamic, lagged endogenous model can be structured as follows, such that the coefficients represent energy demand elasticities:⁵

$$\ln E_t = \alpha + \beta_1 \ln P_t + \beta_2 \ln Y_t + \beta_3 \ln E_{t-1} + \epsilon_t$$

This general econometric approach has been used by others to develop demand elasticities for HDV activity (Gately, 1990; Matos and Silva, 2011). In this paper, we apply a variation on this basic formulation using HDV activity measures as our response variables (CVMT and CFC); and macroeconomic and energy price variables as explanatory variables.

The theoretical underpinnings of this model may be obvious, but are worth mentioning. First, fuel prices directly affect fuel costs, which represent ~30–40% of the trucking sector's costs (Fender and Pierce, 2012) and should have an important influence on decisions that affect energy usage in the sector. One would assume that as fuel prices increase, firms will adjust their operational behavior, logistics, freight rates, or other aspects of their business to reduce VMT and fuel consumption. The coefficient of the fuel price term will provide this price elasticity. Second, as mentioned above, we expect macroeconomic variables such as international trade to effectively represent the general level of economic activity and movement of goods throughout the economy. Lastly, the inclusion of the lagged dependent variable in this equation (E_{t-1}) has particular relevance for an industry that is often connected to routes through longer-term contracts, fixed (immobile) infrastructure, or long-term service agreements.

⁴ The elasticity of diesel prices to gasoline prices for the period 1980–2012 is 1.04, as shown in the SI. Therefore, we have confidence that we can use percentage changes in gasoline prices between 1970 and 1979 as a tool for deriving diesel prices. We also note that during this time the tax rate on both diesel fuel and gasoline was identical (4 cents/gal).

⁵ We note that in Ajanovic et al. (2012) there is a typographical error in Eq. (2) and the natural log is not shown for variable Y_t . We have inserted the natural log in our equation.

Econometric analysis that uses time series data such as ours requires some additional evaluation before model specification can proceed. In particular, nonstationary data and the presence of *unit roots* can affect the credibility of regression results. There are two approaches to handling nonstationary data in multi-variable time series analysis. One approach is to test for unit roots and if they exist, to remove them through differencing. Another approach is to test for *cointegration* of these nonstationary (i.e., integrated) variables. This involves testing whether there is a linear combination of the nonstationary variables that is in fact stationary (Enders, 2004; Hamilton, 1994; Wang and Lu, 2014). If cointegration occurs, then the application of an error correction model (ECM) may be appropriate.

We conducted unit root tests on all variables using an augmented Dickey–Fuller (ADF) test, the details of which are presented in the SI. Based on ADF tests, we could not reject the null hypothesis that unit roots exist for most variables in our data series. This indicates that the data are nonstationary. We corrected for these unit roots using first differences (calculating the difference between data values in year t and year $t-1$). Applying the ADF test to these first-order difference data allowed us to reject the null hypothesis of the existence of unit roots for the differenced series at the 90% confidence level for *CVMT* (p -value 0.089); *CFC* (p -value 0.066); *INTT* (p -value 0.008); and *INTP* (p -value 0.002). We can also reject the null hypothesis for *DPRI* with near 90% confidence (p -value 0.107). These results provide us confidence in the stationarity of our first-differenced data. We also tested for cointegration on our nonstationary datasets by applying Johansen's test, and we determine that cointegration does not exist among the variables used in this paper.⁶

In using first differences for our model specification, readers should note that these log-transformed, first-differenced data essentially represent year-to-year percentage changes. Therefore, our model specification helps identify the relationships between the annual percentage change in our response variable and the annual percentage change in our explanatory variables – a relationship which conveniently represents our sought after elasticities as discussed in the SI.

We also hypothesized that the model specification should reflect possible structural shifts due to two events: (1) data collection and reporting methodology changes that occurred at FHWA for data after the year 2000; and (2) the deregulation of the trucking sector. The first event – changes in FHWA's data collection and reporting methodologies – was discussed above. The second event – the deregulation of the US trucking sector – was driven by the 1980 *Motor Carrier Act* and resulted in important changes in the trucking industry that almost certainly influenced trucking activity (and the relationship between trucking activity and fuel price). For example, deregulation allowed firms to set their own freight rates, removed substantial regulatory barriers to market entry by competitors, and expanded use of fuel surcharges in the trucking sector (GAO, 1981; I.C.C., 1979, 1981; *Motor Carrier Act of 1980, 1980*). The SI for this paper includes the results of Pettit's test for homogeneity, which shows that structural breaks do occur in our response variable datasets and implies that the inclusion of indicator variables may be useful.

Based on these two events, we modified our regression equation to incorporate two indicator (i.e., “dummy”) variables: one for deregulation (*DD*) and one for the change in data collection and reporting methodology (*DM*). We assigned *DD* a value of “0” for the period 1970–1979, and a value of “1” for the period 1980–2012, and assigned *DM* a value of “0” for the years 1970–1999, and a value of “1” for 2000–2012. We integrated these indicator variables into our model for both the intercept term and the interactive terms for P_t and E_{t-1} , leaving us with a final specification consistent with Ajanovic et al. (2012). The following equation provides an example specification for 1970–2012 with *CVMT* as the response variable, *DPRI* as the energy price explanatory variable, and *INTP* as the macroeconomic explanatory variable:

$$\begin{aligned} \Delta \ln CVMT_t = & \alpha + \beta_1 \cdot DD + \beta_2 \cdot DM + \beta_3 \cdot \Delta \ln CVMT_{t-1} + \beta_4 \cdot DD \cdot \Delta \ln CVMT_{t-1} + \beta_5 \cdot DM \cdot \Delta \ln CVMT_{t-1} + \beta_6 \cdot \Delta \ln DPRI_t \\ & + \beta_7 \cdot DD \cdot \Delta \ln DPRI_t + \beta_8 \cdot DM \cdot \Delta \ln DPRI_t + \beta_9 \cdot \Delta \ln INTP_t + \epsilon_t \end{aligned}$$

This specification includes indicator variables both as intercept terms (indicating an overall shift in the response variable) and as interactive terms (indicating a change in the relationship between the response variable and certain explanatory variables). Other explanatory variables have been explored in the literature, including highway lane miles, vehicle capacity and age, labor wages, vehicle price, and macroeconomic indicators such as inventory-to-sales ratios (De Borger and Mulalic, 2012; Matos and Silva, 2011; West et al., 2011). We will return to the incorporation of data such as these later in the paper.

A final element of our analysis includes addressing any outliers that may be due to new FHWA data collection and reporting methodology. In the transformed *CVMT* and *CFC* datasets there exists a point that is ~ 3.5 standard deviations from the mean. Both occur in the late 1990s when we are aware that the FHWA modified data collection and reporting methodologies. These outliers represent the connecting point between two different data collection approaches. Since one of our goals is to capture the impact of the FHWA's new methodology in our time series, we are concerned about annual percentage changes in our response variables up to 1999, *ending* with the data point that reflects the 1998–1999 data; and the annual percentage changes after 2000, *beginning* with the data point that reflects the 2000–2001 data. The 1999–2000 percent change data point is irrelevant, and its inclusion may generate spurious results.⁷ Therefore, we remove this data point from our analysis, but we retain it in the raw dataset available to readers. We also discuss the identification of this point as an outlier using Grubbs test in the SI for this paper.

⁶ The SI presents an analysis with select cointegrated variables to demonstrate a different methodology to use when cointegration occurs.

⁷ Despite the logic presented in this paragraph making the case for removing the outliers, we still conducted analyses with these data present and the results were not much different than those reported below with this outlier removed.

Results

In this section we report our results. For each regression we report the coefficient estimates, their level of statistical significance (p -value), and the adjusted- R^2 value for the model. Additionally, tests for serial correlation, such as Durbin's h -test and the Breusch-Godfrey (BG) test were conducted, and we could reject the existence of serial correlation (detailed results of these tests are found in the SI). Of particular interest below are the coefficient estimates for the explanatory price variable, since these represent price elasticities. Interpretation and discussion of these results are contained in the 'Discussion' section that follows.

We ran our model for combination trucks using VMT and fuel consumption as response variables. We evaluated a wide range of explanatory variable combinations, with the inclusion and exclusion of certain variables, including indicator variables. We also ran the model with the inclusion of other transportation-related data. After a considerable number of trials, based on theory about which variables are important (informed by extant literature discussed above), consideration of whether serial correlation exists, and various tests and metrics to assess the quality of model specification (e.g., adjusted- R^2), one of the best specified models is as follows:

$$\Delta \ln CVMT_t = \alpha + \beta_1 \cdot DM + \beta_2 \cdot \Delta \ln CVMT_{t-1} + \beta_3 \cdot DD \cdot \Delta \ln CVMT_{t-1} + \beta_4 \cdot \Delta \ln DPRI_t + \beta_5 \cdot DD \cdot \Delta \ln DPRI_t + \beta_6 \cdot \Delta \ln INTT_t + \epsilon_t$$

Results for this model are shown in Table 1. All variables are statistically significant at the 95% confidence level, with the exception of the coefficient on fuel price for model (c) which represents a modified specification where we use $INTP$ for the macroeconomic variable and we only run the model for the period 1980–2012, thereby eliminating the deregulation indicator variable. The same models were also run with an adjusted specification that removes the lagged dependent variable on the RHS and results are shown in the SI (and are consistent with those in Table 1).

The model shows positive elasticity (β_6) with respect to international trade ($INTT$), in this case $\sim 17\%$. Similar results are seen when $INTT$ is replaced with $INTP$. The coefficients for fuel price (representing the price elasticity of VMT) is -0.376 prior to deregulation, but adjusts close to zero in recent decades. This is clearly seen in part (c) of Table 1 which only models data from 1980 to 2012 and shows a price elasticity that is essentially zero (0.005). We also note that the negative coefficient on the lagged dependent variable, although counter-intuitive, would be expected if the data are properly de-trended, which they are using our first difference transformation (i.e., a percentage increase in one year would be followed by a percentage decrease in the following year, as shown more clearly in a visual sense in the SI figures).

We conducted similar analyses on fuel consumption (CFC) as we did on $CVMT$, using the following model:

$$\Delta \ln CFC_t = \alpha + \beta_1 \cdot DM + \beta_2 \cdot \Delta \ln CFC_{t-1} + \beta_3 \cdot DD \cdot \Delta \ln CFC_{t-1} + \beta_4 \cdot \Delta \ln DPRI_t + \beta_5 \cdot DD \cdot \Delta \ln DPRI_t + \beta_6 \cdot \ln INTT_t + \epsilon_t$$

Results of this model are shown in Table 2 (again, with results from an alternative specification that removes the lagged dependent variable on the RHS in the SI). The results are similar to results obtained for $CVMT$; that is, we see elasticities of -0.366 in the period 1970–1979, followed by a positive shift post-deregulation. Where the fuel price elasticity was essentially zero after deregulation for $CVMT$, we see that it is slightly positive for CFC (approximately $-0.366 + 0.402 = +0.036$, or 3.6%), a value confirmed in Table 2(c) which shows results for the period 1980–2012 and indicates a slightly positive elasticity (although not statistically different from zero).

We note that the fuel price elasticities presented in these tables represent short-run fuel price elasticities, whereas long-run elasticities can be estimated by dividing our short-run elasticities by one minus the coefficient of the lagged dependent variable term ($CVMT_{t-1}$) (Goodwin, 1992). In these two cases the long-run elasticities are essentially zero. Lastly, other model specifications were evaluated, including those that incorporated other explanatory variables that may affect trucking activity as reported in the literature; however, we did not find any substantial changes in our results, especially with regard to fuel price coefficients. This suggests that our estimates of the fuel price elasticity are robust across different model specifications. Some of these results, including model specifications that do not include a lagged dependent variable as an explanatory variable, are presented in the SI.

Discussion

Our results provide some important insights with respect to fuel price elasticities of combination truck activity. First, the methodology indicator variable (DM) proves significant as an intercept term. This implies that the shift in data collection and reporting that occurred at FHWA led to a structural shift in the time series data as reported by FHWA that is important to consider in future analyses of these data. Additionally, the methodology change at FHWA did not seem to affect the relationship between the response variable and the explanatory variables (i.e., the elasticities), since model specifications that include the DM variable as an interactive term did not indicate a statistically significant response.

Second, the coefficients related to price effects suggest a statistically significant change in price elasticities between a regulatory environment (1970–1979) and a deregulated environment (1980–2012).⁸ Our results indicate negative elasticities ($\sim -35\%$) in the 1970s. Such a condition might be expected in a regulated market where carrier rates were fixed in long-term contracts and increases in the price of oil could have immediate, negative, and significant impacts on a company's

⁸ We note that the significant effect of the deregulation indicator variable proved true even when we substituted crude oil prices for diesel fuel prices.

Table 1

Results of combination truck vehicle miles traveled (CVMT) analysis using diesel fuel price (DPRI) and (a) international trade (INTT) and (b) INTT less petroleum (INTP) as explanatory variables, as well as fixed and interactive effects of indicator variables accounting for deregulation (DD) and shift in data collection methods (DM). Part (c) shows results from 1980 to 2012 (removing deregulation indicator variable).

Variable	Coefficient	Value	Std. error	T-stat	p-value
<i>(a) INTT as explanatory macroeconomic variable</i>					
Intercept		0.037	0.007	5.142	<0.0001
DM	β_1	-0.047	0.010	-4.698	<0.0001
CVMT _{t-1}	β_2	0.478	0.150	3.190	0.003
DD·(CVMT _{t-1})	β_3	-0.728	0.166	-4.399	<0.0001
DPRI _t	β_4	-0.376	0.083	-4.536	<0.0001
DD·(DPRI _t)	β_5	0.383	0.087	4.398	<0.0001
INTT _t	β_6	0.171	0.055	3.087	0.004
Adjusted R ²	0.693				
<i>(b) INTP as explanatory macroeconomic variable</i>					
Intercept		0.036	0.007	5.006	<0.0001
DM	β_1	-0.046	0.010	-4.623	<0.0001
CVMT _{t-1}	β_2	0.487	0.149	3.266	0.003
DD·(CVMT _{t-1})	β_3	-0.732	0.166	-4.423	<0.0001
DPRI _t	β_4	-0.353	0.083	-4.278	<0.0001
DD·(DPRI _t)	β_5	0.369	0.088	4.194	<0.0001
INTP _t	β_6	0.173	0.057	3.059	0.004
Adjusted R ²	0.692				
<i>(c) Analysis from 1980–2012 with deregulation indicator variable removed</i>					
Intercept		0.035	0.008	4.579	<0.0001
DM	β_1	-0.046	0.010	-4.618	<0.0001
CVMT _{t-1}	β_2	-0.250	0.138	-1.804	0.083
DPRI _t	β_3	0.005	0.033	0.157	0.876
INTP _t	β_4	0.210	0.064	3.311	0.003
Adjusted R ²	0.570				

Table 2

Results of combination truck fuel consumption (CFC) analysis using diesel fuel price (DPRI) and (a) international trade (INTT) and (b) INTT less petroleum (INTP) as explanatory variables, as well as fixed and interactive effects of indicator variables accounting for deregulation (DD) and shift in data collection methods (DM). Part (c) shows results from 1980 to 2012 (removing deregulation indicator variable).

Variable	Coefficient	Value	Std. error	T-stat	p-value
<i>(a) INTT as explanatory macroeconomic variable</i>					
Intercept		0.032	0.007	4.440	<0.0001
DM	β_1	-0.044	0.010	-4.219	<0.0001
CFC _{t-1}	β_2	0.561	0.167	3.364	0.002
DD·(CFC _{t-1})	β_3	-0.977	0.198	-4.939	<0.0001
DPRI _t	β_4	-0.366	0.088	-4.171	<0.0001
DD·(DPRI _t)	β_5	0.402	0.092	4.381	<0.0001
INTT _t	β_6	0.141	0.056	2.505	0.018
Adjusted R ²	0.673				
<i>(b) INTP as explanatory macroeconomic variable</i>					
Intercept		0.031	0.007	4.323	<0.0001
DM	β_1	-0.043	0.010	-4.151	<0.0001
CFC _{t-1}	β_2	0.568	0.167	3.403	0.002
DD·(CFC _{t-1})	β_3	-0.981	0.198	-4.943	<0.0001
DPRI _t	β_4	-0.347	0.087	-3.964	<0.0001
DD·(DPRI _t)	β_5	0.390	0.093	4.197	<0.0001
INTP _t	β_6	0.142	0.058	2.449	0.020
Adjusted R ²	0.670				
<i>(c) Analysis from 1980 to 2012 with deregulation indicator variable removed</i>					
Intercept		0.032	0.008	3.934	0.001
DM	β_1	-0.044	0.011	-4.090	<0.0001
CFC _{t-1}	β_2	-0.419	0.158	-2.648	0.014
DPRI _t	β_3	0.038	0.038	1.001	0.327
INTP _t	β_4	0.161	0.069	2.336	0.028
Adjusted R ²	0.519				

bottom line. In high oil price environments, firms would need to cut fuel costs (through VMT reductions or efficient practices such as reduced speed or efficient loading) or risk going out of business. Indeed, situations like this ultimately led to the acceptance and approval for companies to employ fuel surcharges to protect against such oil price increases.

Yet, in the deregulated environment since 1980, our results suggest fuel price *inelasticity* of demand for VMT and fuel consumption. These findings may run counter to economic theory about price responses, yet are not without precedent. For instance, Dahl (2012) in a review of fuel price elasticities globally found that compared to gasoline price elasticities, diesel price elasticities tend to be smaller, insignificant or even positive. Additionally, Matos and Silva (2011), in an analysis for Portugal, found a statistically significant negative elasticity of demand for freight trucking with respect to freight costs (\$/ton-mile), but found a statistically significant positive relationship between oil price (\$/bbl) and freight activity. And Gately (1990) found the relationship between fuel price per mile and US HDV VMT to be statistically insignificant.

Nonetheless these results warrant further discussion. To preface that discussion, readers should keep in mind that trucking VMT (and by association, fuel consumption) is a metric that reflects a larger system of shipper–carrier–receiver interactions, and includes logistics and delivery decisions that affect the behavior of all these stakeholders (Holguín-Veras et al., 2006; Holguín-Veras, 2008, 2011). The “carrier–receiver” relationship is particularly important, and different decisions are observed depending on whether (1) those relationships are highly “integrated” or “independent,” and (2) the market structure is competitive or not (Holguín-Veras, 2008).

In this context we see several factors that may explain the movement toward price inelasticity in a post-regulated environment. One factor may be the prevalent use of fuel surcharges in the US, which allow firms to pass increases in fuel costs to customers and perhaps even profit when fuel prices increase. As part of deregulation and in response to the oil price shocks of the late 1970s, the US government allowed companies to apply a fuel surcharge on their transportation services. This fuel surcharge was designed to reduce the uncertainty that existed with volatile oil prices (I.C.C., 1979, 1981) and to provide a transparent method by which shippers, carriers, and customers could calculate and adjust rates according to this volatility (which threatened the health of some companies engaged in the long-term shipping contracts that existed in the sector). Though calculation of the fuel surcharge is not regulated (EIA, 2014a), a typical formula involves three factors: a base fuel price –a threshold above which a fuel surcharge will be applied (typically \$1.25/gal); a metric for fuel economy (typically ~6 mpg) (Rutherford, 2012), and the current fuel price, which is published weekly by the US DOE. The fuel surcharge is calculated by subtracting the base fuel price from the current fuel price (adjusted weekly based on federal fuel prices reported by DOE), and dividing the remainder by mpg (Rutherford, 2012). The result is a fuel surcharge that all carriers can apply.

Readers may see the incentives this system creates. If a fleet is more efficient than 6 mpg, the fuel surcharge may result in increased profit to the firm. For example, under a price of \$4.00/gal with a base rate of \$1.25/gal, the fuel surcharge at 6 mpg would be $[\$4.00 - 1.25]/6 = \$0.458/\text{mile}$.⁹ This is the amount that the carrier can charge additionally as a fuel surcharge. Yet, if the firm's fleet average fuel economy is actually 7 mpg, then the real incremental cost is $[\$4.00 - 1.25]/7 = \$0.393/\text{mile}$. The company can earn \$0.065/mile profit using more efficient vehicles. Thus, a higher fuel price, in the short term, may negate any incentive to reduce VMT or engage in other fuel efficient practices, perhaps even driving service expansion and possibly increasing travel services. The surcharge system does create incentives for trucking companies to “beat” the 6 mpg target, however, and doing so would allow firms to profit on what are already very slim margins (3–10%) (Biery, 2014; Sutherland and Koepke, 2012). The actual response to and consideration of fuel surcharges by trucking firms in the context of changing fuel prices is uncertain, and warrants further research. Regardless of trucking firm responses, we recognize that the US fuel surcharge system passes on fuel price changes to customers, and theory would suggest that increases in service price would reduce demand for freight services (and vice versa).

A second factor influencing price elasticities may be the ability of firms to cover rising fuel costs with lower labor or capital costs without affecting VMT or fuel consumption (i.e., substitution effects). For context, consider that in 2011 fuel and oil comprised ~35% of freight carriers' operational costs on average, while driver wages and benefits comprised ~36%, and vehicle purchase and lease payments comprised ~11% (ATRI, 2012). In a high fuel price environment firms may be induced to cut costs from other inputs of production in order to maintain services. Similarly, firms may also reduce or delay capital expenditures (e.g., purchasing new trucks) in a high fuel price environment.

Additionally, research has shown that firms may invest in trucks with a higher capacity in response to higher fuel prices (De Borger and Mulalic, 2012), which may allow firms to move the same amount of goods at a lower cost per ton-mile—and allow them to reduce the cost of their services, further insulating customers from effects of higher fuel prices. Though our dataset lacks detailed information on the average capacity of freight trucks, we note that the ratio of sales of Class 8 to Class 7 trucks has increased from 1.1:1 in 1986 to over 4:1 in 2012 (ORNL, 2013b), suggesting that firms may be responding to higher fuel prices by investing in larger trucks that consume less fuel per ton-mile or by increasing the load capacity per truck. In fact, our results showing an inelastic fuel price demand elasticity for VMT, but a slightly positive fuel price demand elasticity for fuel would be consistent with an environment where higher fuel prices trigger more heavily loaded trucks

⁹ Firms may formulate fuel surcharges in a number of ways (surcharges are not regulated), including as a percentage increase to base freight rates, or per-mile. The structure may vary by firm or even within a firm; for instance Conway (#3 in revenue in 2011, behind UPS and FedEx) applies fuel surcharges per-mile for volume shipments, or as a percentage basis—which differs for LTL (less-than-truckload) and TL (truckload) shipments. (http://www.con-way.com/en/tools_pricing/freight/fuel_surcharge/historical_surcharge_data/). Though we use a per-mile fuel surcharge in our example here for purposes of clarity and simplicity, we note that the potential incentive/profit created by the fuel surcharge is relevant regardless of the structure of the fuel surcharge, where a fleet's efficiency allows the surcharge to bring in revenue exceeding fuel cost expenditures.

running similar routes (i.e., VMT remains the same, tonnage increases, and fuel consumption increases slightly due to heavier loading). Further research (both qualitative and quantitative) on the actual decision making behavior of firms in this sector is necessary in order to better understand the sector's fuel use and pricing dynamics. That research can help us determine the significance of the relationships introduced above after controlling for other explanatory factors.

Finally, theory suggests that in response to higher fuel prices, truck drivers would adjust fuel consumption through more efficient driving behavior, such as reduced speeds or reduced idling, or chose more efficient routes to reduce VMT. However, as recognized by [Vernon and Meier \(2012\)](#), the vast majority of the freight trucking sector is comprised of common carriers (44%) or private motor carriers (42%), in which hired drivers do not pay fuel costs, and so suffer from the "principal-agent" problem where drivers lack strong incentives to modify behaviors in response to fuel prices. That is, although drivers have the ability to control such things as the speed of the vehicle or the extent of idling, in the absence of a financial incentive to do so, drivers are unlikely to make any such changes. More research involving analysis of truck driver attitudes and behavior with respect to fuel prices is needed to explore the strength of this principal-agent problem in the trucking sector.

We can also consider our findings from the demand perspective—i.e., from the lens of the freight customer or "receiver." If fuel price increases were passed on to customers in the form of higher freight rates or fuel surcharges, we would expect these customers to respond by reducing their demand for freight services. However, one has to consider freight trucking itself as an input to production. Freight transportation is a key input in many supply chains, and inelastic demand responses to freight rates may exist if: (1) these rates are trumped by service requirements; (2) alternative forms of transporting goods (alternative modes) are not available; or, (3) decisions are driven by existing infrastructure and cultural conditions (such as highways and just-in-time logistics). Fuel surcharges may have little effect on a customer's decision to get materials and product where it needs to go, especially when all other competitors in the trucking sector are charging a similar fuel surcharge level and no other shipping alternatives exist. Shippers or receivers are left with a Hobbesian Choice of paying more for a shipment or no shipping at all.

To complicate matters a bit further, all of the decision making theory implied above is influenced by the level of competitiveness in the market. A highly competitive market, as might be found in an urban area, would seem to give much power to receivers ([Holguín-Veras, 2008](#)), whereas a less competitive market may allow for carriers to dictate costs and terms of delivery with more authority. The decision making behavior of shippers, carriers, and receivers in the context of fuel efficiency standards and under different market structures is an important area for future research.

Conclusion

In this paper we estimated the fuel price elasticity of HDV activity (VMT) and HDV fuel consumption for combination trucks. Our results suggest that we are in a period of time where fuel price elasticities for US combination trucking VMT and fuel consumption are near zero. We hypothesize this may be due to: (1) the structure of the existing fuel surcharge system in the US, which may negate any incentive for firms to reduce travel or energy consumption in response to higher fuel prices; (2) adjustments in other modifiable operational costs, such as labor or capital expenses, by trucking firms; (3) the potential for the "principal-agent" problem to affect driver behavior; or (4) the nature of freight transportation as a product and its characteristics that lead to an inelastic demand response to price changes.

We conducted this analysis in the context of recent regulations promulgated in the US which will improve the efficiency of HDVs and thus reduce fuel costs. A potential unintended consequence of reduced fuel costs is an increase in HDV activity and thus energy consumption—i.e. the "rebound effect"—which could diminish energy and emissions benefits of efficiency improvements. One can use the elasticities presented in this paper as rebound proxies under certain assumptions, including the assumption that firms respond to fuel price changes and fuel efficiency changes in an identical manner and that responses to fuel cost increases and reductions are symmetric ([Winebrake et al., 2012](#)). We would like to emphasize that these assumptions are nontrivial, and there is some suggestive evidence in the literature that these assumptions may not hold; further research is needed to test their relevance in the HDV truck sector (e.g. [Gately, 1993](#); [Dargay and Gately, 1997](#); [Greene, 2012](#); [Hymel and Small, 2015](#); [Sentenac-Chemin, 2012](#)).

Additional research and better data are needed to estimate the rebound effect more directly using econometric approaches. Such approaches would ideally measure the change in energy consumption or activity in response to an increase in fuel efficiency ([Winebrake et al., 2012](#)). However, robust HDV fuel efficiency (MPG) time-series data are lacking, primarily because FHWA MPG data are derived in part from aggregate fuel consumption and VMT data, and the use of this derived MPG data introduces issues of interdependence that would need to be addressed. The validation of these data is also problematic given the dearth of available data from other sources on this topic.

Nevertheless, our results suggest the possibility that HDV fuel economy regulations can reduce energy consumption proportionately with negligible induced increases in HDV VMT activity and energy use. Results also suggest that fuel pricing policies such as fuel taxes may not result in significant reductions in HDV travel or energy use, at least within the price ranges evaluated in our analysis. This may have important implications for policies intended to minimize congestion, emissions, or other negative externalities of HDV vehicle use. Finally, more research is needed to gain an understanding of the responses undertaken by trucking firms and freight customers in response to fuel price changes, efficiency improvements, fuel surcharges, and freight rate changes at the aggregate level.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.trd.2015.04.006>.

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