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Fuel price elasticities for single-unit truck operations in the United States

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ABSTRACT

This paper provides fuel price elasticity estimates for single-unit truck activity, where single-unit trucks are defined as vehicles on a single frame with either (1) at least two axles and six tires; or (2) a gross vehicle weight greater than 10,000 lb. Using data from 1980 to 2012, this paper applies first-difference and error correction models and finds that single-unit truck activity is sensitive to certain macroeconomic and infrastructure factors (gross domestic product, lane miles expansion, and housing construction), but is not sensitive to diesel fuel prices. These results suggest that fuel price elasticities of single unit truck activity are inelastic. These results may be used by policymakers in considering policies that have a direct impact on fuel prices, or policies whose effects may be equivalent to fuel price adjustments.

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Introduction

Over the past several decades, the relative contribution of heavy-duty vehicles (HDV) to total transportation energy use and emissions in the United States (US) has increased. The share of highway vehicle miles traveled (VMT) attributable to HDVs increased from 6% in 1970 to 9% in 2011 (BTS, 2014a), while the share of highway vehicle energy consumption by HDVs nearly doubled from 13% to 25% (BTS, 2014b,c,d,e). With this growing energy use comes increased greenhouse gas (GHG) emissions and other pollutants, and HDVs are now a focus of new regulatory actions aimed at improving fuel efficiency and reducing GHG emissions from the transportation sector.

Unlike the light-duty vehicle (LDV) sector, HDVs never had to meet fuel efficiency standards in the US. This changed in 2011 when the US Environmental Protection Agency (EPA) and the US National Highway Transportation and Safety Administration (NHTSA) jointly established GHG emissions and fuel efficiency standards for US HDVs for the first time (EPA and NHTSA, 2011). The standards, focused on truck model years 2014–2018, regulate GHGs (measured in gCO₂/ton-mile) and fuel consumption (measured in gallons per thousand ton-miles) and aim to reduce lifetime fuel consumption and emissions by 20% for combination (i.e. freight) trucks and 10% for vocational (mostly single-unit) trucks (The White House, 2014a). The US recently announced plans to extend these regulations beyond model year 2018 (The White House, 2014b).

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However, technical efficiency improvements do not always meet engineering expectations for fuel consumption and emissions reductions due to what is called the “rebound effect” (Berkhout et al., 2000; De Borger and Mulalic, 2012; Greene, 2012; Greene et al., 1999; Greening et al., 2000; Hymel and Small, 2015; Matos and Silva, 2011; Small and Van Dender, 2005; Sorrell and Dimitropoulos, 2007; Winebrake et al., 2012). The rebound effect refers to the phenomenon whereby technical efficiency improvements effectively reduce the fuel cost of an energy service, thereby inducing increased activity or demand for the service, “taking back” some of the intended energy savings.¹ Policymakers must understand the anticipated magnitude of the rebound effect to better estimate the actual changes in energy consumption and emissions in response to technical efficiency improvement standards.

Estimating the rebound effect for the HDV sector is challenging for a variety of reasons. In addition to reasons discussed in previous work (Winebrake et al., 2012), 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 HDV VMT – 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 builds off new methodological approaches recently applied to combination truck data to estimate fuel price elasticities of single-unit truck activity (measured in VMT) (Winebrake et al., 2015). The paper applies both a first-difference model and an error correction model (ECM) using data from 1980 to 2012. By themselves, these calculated elasticities provide valuable information for evaluating the impact of fuel price changes (either market-driven or policy-driven). However, in combination with other assumptions these elasticities may also provide insights into rebound effects under certain limiting conditions (Winebrake et al., 2012).

The paper is divided into five main sections. The next section (‘Background’) provides context surrounding the research question. That is followed by a ‘Data and methodology’ section, which presents the data and modeling approach used; and ‘Results’ and ‘Discussion’ sections that present our results and discuss their importance, respectively. We end with a ‘Conclusion’ section that provides greater context for our results and identifies areas of future research.

Background

Energy consumption in the US heavy-duty vehicle sector

The HDV sector in the US may be categorized by vehicle sub-sectors. For our purposes, we follow US practice and divide the sector into “combination trucks” or “single-unit trucks.” Combination trucks include “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, 2013). Single-unit trucks include “single frame trucks that have 2 axles and at least 6 tires or a gross vehicle weight rating exceeding 10,000 lbs” (FHWA, 2013a), and include for instance, refuse trucks and local delivery trucks.

As shown in Figs. 1 and 2, miles traveled and fuel consumption for both combination and single-unit trucks have been increasing over time, with the exception being the aftershocks of the 2008 recession, which reversed the upward growth trends exhibited since 1980.² The figures also show that single-unit trucks have made up a fairly consistent proportion of VMT and fuel consumption in the HDV sector since 1980. For example, in 1980 single-unit trucks made up about 37% of HDV VMT and 35% of HDV fuel consumption; in 2012, single-unit trucks made up about 39% of HDV VMT and 34% HDV fuel consumption. Since the HDV sector consumes about 25% of all energy used in the transportation sector in the US (BTS, 2014b,c,d,e), we estimate that single-unit trucks and combination trucks are responsible for ~8% (0.34×0.25) and ~17% (0.66×0.25) of that total energy consumption, respectively.

Fuel price elasticities and rebound effects in the literature

As discussed in previous work (Winebrake et al., 2012), the vast majority of literature examining rebound effects and fuel price elasticities of vehicle travel demand focuses on LDVs (Dahl, 2012; Espey, 1998; Graham and Glaister, 2004; Greene, 2012; Litman, 2013; Poor et al., 2007). Fuel price elasticities of LDV travel demand are typically in the range of –0.10 to –0.30, though research has indicated these elasticities may change over time (Brons et al., 2008; Dahl, 2012; Goodwin et al., 2004; Greene, 2012; Li et al., 2014; Litman, 2013). Unfortunately, because the HDV sector is quite different than the LDV sector – namely due to reasons related to vehicle ownership (individuals vs. firms) and incentives (maximizing consumer utility vs. profit maximization and cost minimization) (Berkhout et al., 2000) – LDV rebound effect estimates cannot be applied to the HDV sector with any confidence.

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 Figs. 1 and 2 demonstrate a data collection issue that occurs in the 1999–2000 period and reflects a methodological shift in how the US FHWA collected data from the trucking sector. This shift is statistically important and is addressed in the methodology section of this paper.

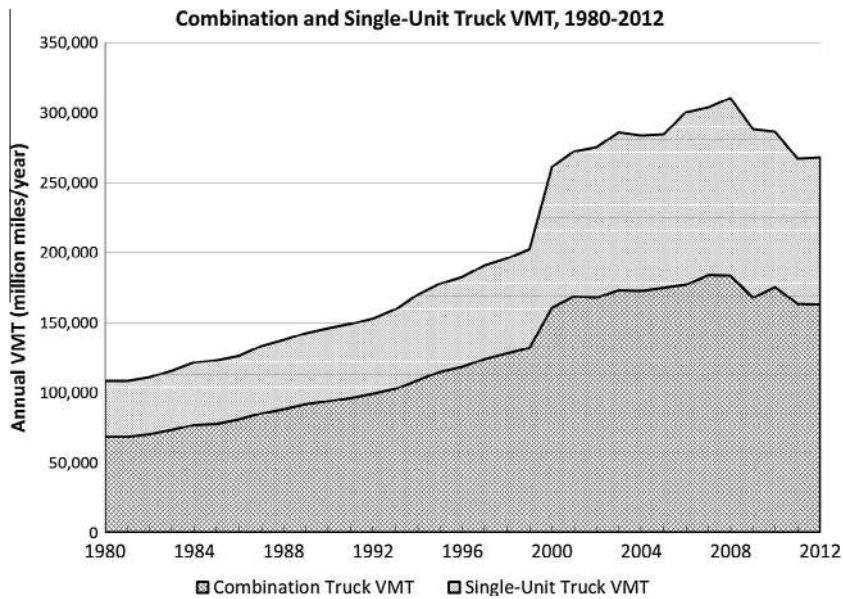


Fig. 1. Combination and single-unit truck vehicle miles traveled in the US, 1980–2012.

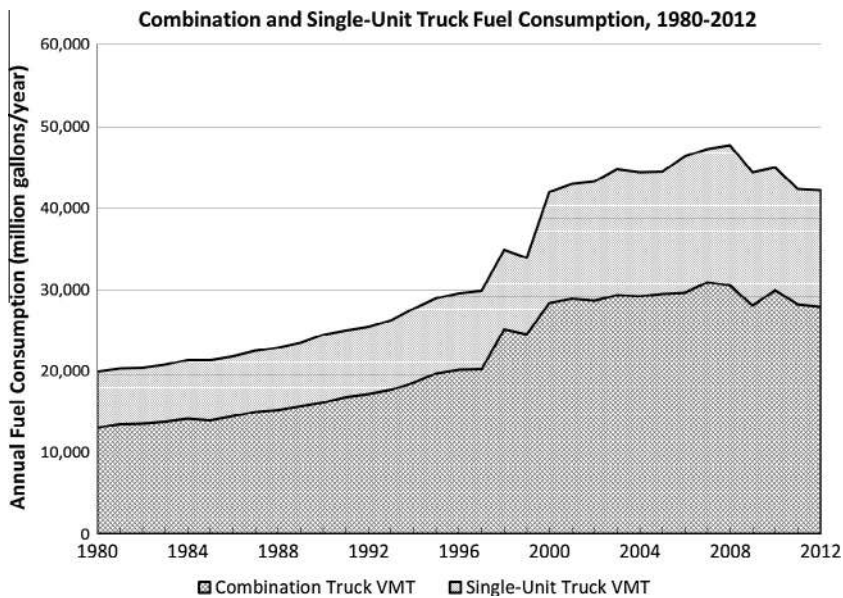


Fig. 2. Combination and single-unit truck fuel consumption (million gallons per year) in the US, 1980–2012.

The literature examining fuel price elasticities in the HDV sector is comparatively scarce, is biased toward combination trucks (long freight hauls), and describes estimates that are made indirectly as an outcome of other research. For instance, West et al. (2011), in estimating the determinants of demand for HDV freight in the US, estimated the elasticity of HDV freight activity with respect to fuel price as -0.05 ; however, West et al. used ton-miles as the measure of freight activity, and there are important limitations with respect to US ton-mile data, so we are hesitant to place a high level of confidence in this estimate.³ In another study, Guerrero (2014) used *freight price* elasticities of demand (percent change in demand for

³ The Bureau of Transportation Statistics (BTS) reports ton-mile data for “freight trucks” in Table 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.

freight in response to a change in freight rates) to approximate HDV *trips* in a simulation model. That study reports a rebound effect of 31–36%. However, if one drills down into the primary sources for the study's elasticity estimates, one finds a reliance on freight price elasticities from research conducted decades prior or in contexts that are quite different than the US transportation sector.⁴ Additionally, any literature that does exist focuses on large-scale freight movements that are dominated by combination trucks and may not be applicable to the single-unit (vocational) trucking sector.

In our own recent work, which adjusts for some data anomalies observed in Figs. 1 and 2, we find fuel price elasticities of combination truck VMT and combination truck fuel consumption to be essentially zero in recent decades (Winebrake et al., 2015). This paper applies the methodology previously developed for the combination truck sub-sector to evaluate fuel price elasticities for single-unit trucks, as discussed in the following section.

We recognize that fuel price elasticities are not a direct measure of the rebound effect in the context of fuel efficiency regulations. Previous work on this topic points out a number of conditions that must be met for analysts to use fuel price elasticity estimates as proxies for the rebound effect (Winebrake et al., 2012). Nevertheless, the two measures are related and uncovering fuel price elasticities for the HDV sector may help inform further discussion about rebound effects due to efficiency improvements in that sector. We discuss this more in later sections of this paper.

Data and methodology

Data

Data for this analysis cover the period 1980–2012 and contain variables that may influence single-unit truck activity as measured by VMT (SVMT). This SVMT, along with single-unit fuel consumption, is shown in Fig. 3 and represents the response variable for our econometric approach. Fig. 4 depicts trends in SVMT with GDP per capita and diesel fuel price (DPRI) for the period 1980–2012. Vehicle miles traveled are estimated by the US Department of Transportation (DOT) FHWA (FHWA, 2011, 2013a), which reports annual aggregate miles traveled by vehicle type in Table VM-1 of their annual *Highway Statistics* report.⁵

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 1980–1999 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 that are available to readers in the [Supplementary Information \(SI\)](#) to this paper. 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 choice of explanatory variables to include in the model was guided by the extant literature on the economic drivers of HDV activity, including recent work by Winebrake et al. (2015), as well as exploratory data analysis. For this paper, in addition to diesel fuel price (DPRI), we considered other macroeconomic variables that are contained in the dataset available to readers in the [SI](#). The variables used in the final specification of the model are discussed in the next section.

Model specification

The model used in this study builds off econometric approaches based on work by previous authors (Ajanovic et al., 2012; Gately, 1990; Matos and Silva, 2011; Winebrake et al., 2015). That work consists of applying a model of the general form

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

⁴ Guerrero (2014) relies on Graham and Glaister (2004) for elasticity estimates. Yet, Graham and Glaister (2004) begin their analysis of the trucking sector by discussing the difficulty in dealing with the heterogeneity of the industry and previous studies of elasticity. They rely on Oum (1979), Friedlaender and Spady (1980), Lewis and Widup (1982), and Levin (1978) as examples – each covering an era or set of commodities that may not be relevant to today. They point out explicitly the wide variation of estimates (even for these older studies), by region and by commodity type. They also rely on Beuthe et al. (2001) which showed “tremendous differences” in elasticities depending on commodity and length of trip. Beuthe et al. (2001) was reviewed in Winebrake et al. (2012) which notes that the Beuthe et al. estimates were based on simulation analyses of the Belgian transportation network and there are numerous caveats to their estimates that they themselves are very open about. Therefore, the “rebound effect” that emerges from Guerrero (2014) is actually based on an approximation and simplification of estimates of elasticities from Graham and Glaister (2004), which is further based on studies that are either old (1970s or 1980s), measure different types of elasticities, are based on regions other than the US, and consist of simulation results as opposed to econometric analyses. Problems with using these types of elasticities were discussed in Winebrake et al. (2012).

⁵ Ideally, we would like to conduct our analysis with both VMT and vehicle ton-miles as response variables, since the latter could capture operational changes that VMT alone does not capture. However, data on vehicle ton-miles are not adequate or reliable for our time series analysis. Readers should note that firms may make changes in the short run to their operations that affect vehicle ton-miles but not VMT (for example, by making adjustments in vehicle loading). However, because VMT is highly correlated with fuel consumption (and therefore emissions), we believe the use of VMT in our analysis provides useful information to better understand relationships between fuel prices and emissions. Nevertheless, readers should not use our elasticity estimates for VMT interchangeably with vehicle ton-miles.

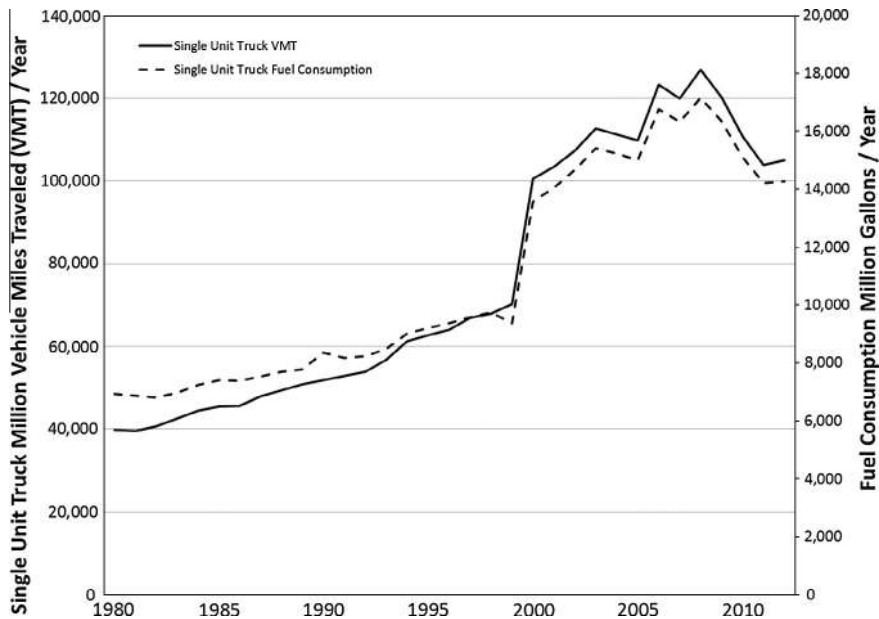


Fig. 3. Single-unit truck vehicle miles traveled and fuel consumption, 1980–2012.

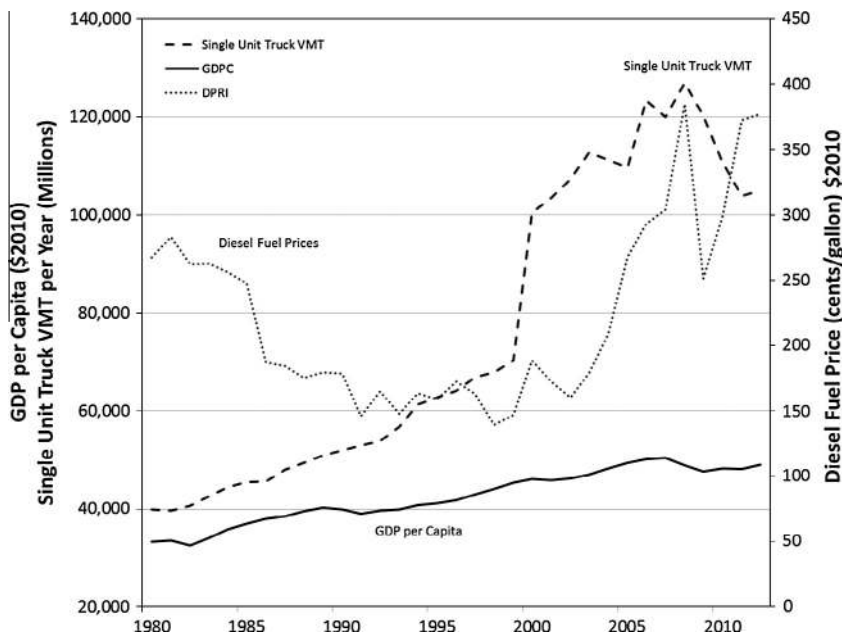


Fig. 4. Single-unit truck VMT, GDP per capita (\$2010), diesel fuel price (\$2010), 1980–2012.

where energy demand (E_t) is a function of price (P_t), income (Y_t), and a lagged demand (E_{t-1}). Evaluating the coefficient on the fuel price term allows one to estimate the fuel price elasticity of demand for energy consumption. This basic model was refined in more recent work analyzing fuel price elasticities for combination truck VMT by these authors (Winebrake et al., 2015) using a first difference model that addressed concerns about nonstationary data and included indicator variables to reflect major shifts in data collection methodologies or external influences (e.g., deregulation in the trucking sector). Readers are pointed to the Winebrake et al. (2015) work for more details on this general model development.

After a considerable number of trials, based on theory about which variables are important (informed by extant literature discussed above), evidence of serial correlation, and various tests and metrics to assess the quality of model specification (e.g., adjusted- R^2), we found the best specified model consisted of the following explanatory variables in addition to

DPRI: real gross domestic product (*GDP*), total U.S. roadway lane-miles (*LAMI*), and residential housing units under construction (*HOUC*). Further testing indicates the results are robust to alternative specifications.

Our first step in model specification was to analyze the time series properties of the model variables (i.e., is there evidence of *unit roots*?). We conducted unit root tests on all variables using a KPSS test (the results are contained in the [SI](#) for this paper). The results of those tests reject the null hypothesis that the data were stationary, consistent with recent analyses (Winebrake et al., 2015).

There are at least two common approaches to handling nonstationary data in multi-variable time series data. One approach is to convert nonstationary data into stationary data through differencing. A second approach is to test for cointegration of 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 exists, then the application of a two-step ECM may be appropriate. In this paper, we present the results using both approaches.

In the first instance, we corrected for unit roots using first differences (calculating the difference between data values in year t and year $t-1$). Applying the KPSS test to these first-order differenced data, we failed to reject the null hypothesis of stationarity at the 5% significance level for all variables used in the model: *SVMT* (p -value 0.158); *DPRI* (p -value 0.191); *GDP* (p -value 0.540); *LAMI* (p -value 0.093), and *HOUC* (p -value 0.396), which supports the use of first-differences in regression analysis. The following equation provides an example first-difference model specification with *SVMT* as the response variable and with the inclusion of an indicator variable (*DM*) representing a data collection methodological change occurring between 1999 and 2000.

$$\Delta \ln(SVMT_t) = \alpha + \beta_1 * DM + \beta_2 * \Delta \ln(DPRI_t) + \beta_3 * \Delta \ln(GDP_t) + \beta_4 * \Delta \ln(GDP_{t-1}) + \beta_5 * \Delta \ln(LAMI_t) + \beta_6 * \Delta \ln(HOUC_t) + \epsilon_t$$

In using first differences for our model specification, readers should note that these log-transformed, first-differenced data represent year-to-year percentage changes, and our model specification identifies the relationships between the annual percentage change in our response variable and the annual percentage change in our explanatory variables – i.e., our sought after elasticities.

Using the alternative (ECM) approach, we tested for cointegration by applying Johansen's test, and our results fail to reject the null hypothesis of a cointegrating relationship among the explanatory variables used in this paper (results are included in the [SI](#)). Cointegration allows us to apply an ECM, following the work of Wang and Lu (2014), among others. The first step in constructing an ECM is to run a regression to estimate the error term (μ) in the following equation:

$$\ln(SVMT_t) = \alpha_0 + \alpha_1 * DM + \alpha_2 * \ln(DPRI_t) + \alpha_3 * \ln(GDP_t) + \alpha_4 * \ln(GDP_{t-1}) + \alpha_5 * \ln(LAMI_t) + \alpha_6 * \ln(HOUC_t) + \mu$$

The estimated residual series $\hat{\mu}$ is then used as the error correction term (*ecm*) in the following ECM:

$$\Delta \ln(SVMT_t) = \beta_0 + \beta_1 * DM + \beta_2 * \Delta \ln(DPRI_t) + \beta_3 * \Delta \ln(GDP_t) + \beta_4 * \Delta \ln(GDP_{t-1}) + \beta_5 * \Delta \ln(LAMI_t) + \beta_6 * \Delta \ln(HOUC_t) + \gamma ecm_{t-1} + \epsilon_t$$

A final note is required regarding the possibility of outliers in the dataset due to new FHWA data collection and reporting methodologies. In the transformed *SVMT* data there is an apparent outlier between the years 1999 and 2000, when we are aware that the FHWA modified data collection and reporting methodologies. The *SVMT* data clearly and unnaturally shift up at this point (see [Fig. 3](#)), and the percent increase from 1999 to 2000 is ~36%. Obviously, the amount of miles traveled by single-unit trucks did *not* increase by 36% in one year. Instead, this outlier represents 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. Therefore, we remove this data point from our analysis. In addition to this obvious outlier for *SVMT*, we identified and removed two outliers from *LAMI*, as discussed in the [SI](#) of this paper. No other outliers were found.

Results

We ran first-difference models and ECMs to evaluate the fuel price elasticity of *SVMT* for the period 1980–2012. We evaluated dozens of explanatory variable combinations, with the inclusion and exclusion of certain variables, including indicator variables. A number of those results are contained in the [SI](#) for this paper; in this section we summarize our most relevant results, reporting 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 the Durbin–Watson test, Durbin's h -test, and the Breusch–Godfrey (BG) test were conducted. Evidence for serial correlation was found in some of our model specifications, but not in our best-specified models presented below. Of particular interest below are the coefficient estimates for the explanatory price variable (*DPRI*), since these represent fuel price elasticities of *SVMT*. Interpretation and discussion of these results are contained in the next section.

The best-specified first-difference model for *SVMT* that emerged from our analysis is as follows:

$$\Delta \ln(SVMT_t) = \alpha + \beta_1 * DM + \beta_2 * \Delta \ln(DPRI_t) + \beta_3 * \Delta \ln(GDP_t) + \beta_4 * \Delta \ln(GDP_{t-1}) + \beta_5 * \Delta \ln(LAMI_t) + \beta_6 * \Delta \ln(HOUC_t) + \epsilon_t$$

Results for this model are shown in [Table 1](#). The adjusted- R^2 is 0.320. The fuel price ($DPRI$) coefficient equals 0.044 but is not statistically significant ($p = 0.445$). Therefore, although we show slightly positive price elasticity, we cannot say that the fuel price elasticity of $SVMT$ is statistically different from zero. The same model was also run with the lagged dependent variable on the RHS (presented in the [SI](#)), but the adjusted- R^2 decreased to 0.297 and the coefficient for the lagged dependent variable was not significant ($p = 0.767$).⁶

The best-specified ECM for $SVMT$ that emerged from our analysis is as follows:

$$\Delta \ln(SVMT_t) = \beta_0 + \beta_1 * DM + \beta_2 * \Delta \ln(DPRI_t) + \beta_3 * \Delta \ln(GDP_t) + \beta_4 * \Delta \ln(GDP_{t-1}) + \beta_5 * \Delta \ln(LAMI_t) + \beta_6 * \Delta \ln(HOUC_t) + \gamma ecm_{t-1} + \varepsilon_t$$

Results for this model are shown in [Table 2](#). The adjusted- R^2 is 0.415, and all explanatory variables are statistically significant at the 90% confidence level except GDP ($p = 0.112$) and the fuel price ($DPRI$) coefficient, which has a value of 0.029 ($p = 0.593$). Once again, we obtain a slightly positive fuel price elasticity for $SVMT$, but we cannot say that the fuel price elasticity of $SVMT$ demand is statistically different from zero. The same model was also run with the lagged dependent variable on the RHS (presented in the [SI](#)). The adjusted- R^2 increased slightly to 0.418, but the coefficient for the lagged dependent variable and a number of other variable coefficients were not significant at the 90% confidence level and the Durbin's h-test suggested strong evidence of serial correlation.

Discussion

There are several important results that emerge from this analysis. First, we see that in both the first-difference model and the ECM, the coefficient for $DPRI$ is slightly positive – however, it is not statistically significant and we cannot say with statistical confidence that the actual value is different than zero. In fact, in every model we attempted the coefficient for $DPRI$ was similar: slightly positive with an inability to reject the null hypothesis that the value was zero. As might be visually apparent in [Fig. 4](#), while $DPRI$ varied considerably during recent decades, $SVMT$ tended to behave in a manner that was driven by other, perhaps more localized, factors. Our results suggest that the influence of diesel fuel prices on single-unit truck travel (at least in the fuel price ranges studied) is actually small to non-existent, and that other factors are driving $SVMT$ changes.⁷

In theory, an inelastic environment for single-unit trucking operations could occur when single-unit trucks operate in a competitive carrier environment where receivers dictate terms and conditions of travel – no matter what the price for fuel (within a given range, of course). This theory was discussed in the context of combination trucks in [Winebrake et al. \(2015\)](#) building off the work of [Holguín-Veras et al. \(2006\)](#) and [Holguín-Veras \(2008, 2011\)](#). A convincing alternative hypothesis could also be made that inelasticities would be observed in a non-competitive market, where carriers could easily pass along any fuel price increases to customers without impacting demand. Such an argument was presented in [Winebrake et al. \(2015\)](#) in the case of combination trucks. There is no single answer to the question of what types of markets (competitive or non-competitive) single-unit trucks operate, as the answer is a function of location and type of service provided, among others. For example, we would expect greater levels of competition among carriers in high-density urban areas, but even there the type of service provided may have limited competition (e.g., waste haulers). More research (both quantitative and qualitative) is needed directed at the local level to better understand how competition and local conditions affect carrier decision-making.

Another theory discussed in [Winebrake et al. \(2015\)](#) is that of split incentives which may also help explain our results. In such a case, the incentives that affect the behavior of drivers are not consistent with those affecting firm owners. Drivers may not be as concerned about fuel prices and their behavior may be affected by other factors that lead to higher VMT or fuel consumption. For example, a driver paid by the delivery may be more interested in delivering those goods as quickly as possible, and less concerned about saving fuel by traveling at lower speeds. The impact of the split incentive effect depends on the structure of the carrier firm and the service it provides and more research is needed to better understand these behavioral effects in the single-unit truck sector.

Our results are also 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, although this result may be unreliable because the time series properties of the variables in the model may not have been adequately addressed.

⁶ A robustness test was conducted to account for potential reverse causality using approaches discussed by [Davis and Kilian \(2011\)](#) and [Li et al. \(2014\)](#). In particular, we ran a structural model using global oil prices as an instrument variable and our results were consistent with those in [Table 1](#), with a coefficient on the fuel price variable ($DPRI$) of 0.042 that was not statistically significant.

⁷ As an aside, we point out that our results have potential impacts for interpreting analyses on LDV fuel price elasticities. Given the inelasticity in the single-unit HDV sector that we uncover here, fuel price elasticity studies for LDVs that are based on fuel consumption data and that do not disaggregate HDVs from LDVs will obtain results that are likely biased toward zero. Analysts need to be aware of this possible bias when evaluating LDV elasticity results.

Table 1

Results of single-unit truck vehicle miles traveled (*SVMT*) first-difference analysis using diesel fuel price (*DPRI*), gross domestic product (*GDP*), total U.S. roadway lane-miles (*LAMI*), and residential housing units under construction (*HOUC*) for the period 1980–2012. An indicator variable (*DM*) accounts for a change in the methodology used to estimate *SVMT* beginning with the year 2000.

Variable	Coefficient	Value	Std. error	T-stat	p-Value
Intercept		0.037	0.022	1.671	0.110
Indicator variable (<i>DM</i>)	β_1	-0.037	0.017	-2.167	0.042
Fuel price (<i>DPRI</i>)	β_2	0.044	0.056	0.778	0.445
Gross domestic product (<i>GDP</i>)	β_3	-1.055	0.564	-1.870	0.076
GDP_{t-1}	β_4	0.690	0.414	1.669	0.110
Lane miles (<i>LAMI</i>)	β_5	4.419	2.756	1.603	0.124
Housing construction (<i>HOUC</i>)	β_6	0.174	0.069	2.515	0.020
Adjusted R^2	0.320				

Table 2

Results of single-unit truck vehicle miles traveled (*SVMT*) ECM analysis using diesel fuel price (*DPRI*), gross domestic product (*GDP*), total U.S. roadway lane-miles (*LAMI*), and residential housing units under construction (*HOUC*) for the period 1980–2012. An indicator variable (*DM*) accounts for a change in the methodology used to estimate *SVMT* beginning with the year 2000.

Variable	Coefficient	Value	Std. error	T-stat	p-Value
Intercept		0.028	0.021	1.367	0.187
Indicator variable (<i>DM</i>)	β_1	-0.032	0.016	-1.940	0.067
Fuel price (<i>DPRI</i>)	β_2	0.029	0.053	0.543	0.593
Gross domestic product (<i>GDP</i>)	β_3	-0.882	0.530	-1.665	0.112
GDP_{t-1}	β_4	0.691	0.384	1.799	0.087
Lane miles (<i>LAMI</i>)	β_5	5.171	2.582	2.003	0.059
Housing construction (<i>HOUC</i>)	β_6	0.176	0.064	2.729	0.013
Error correction Term (ECM_{t-1})	γ	-0.353	0.168	-2.098	0.049
Adjusted R^2	0.415				

We should also comment on the elasticities that emerge for other explanatory variables (*HOUC*, *LAMI* and *GDP*) in [Tables 1 and 2](#). In both the first-difference model and the ECM, we observe a positive, and significant, relationship between *HOUC* and *SVMT*. This is expected due to the role that single-unit trucks play in both enabling the construction of new housing units and supplying these new units with various commodities.

We also observe a strong positive influence of *LAMI* on *SVMT* (with elasticities on the order of 4–5). The *LAMI* coefficient was not significant at the 90% confidence level in the first difference model but it would be significant at the 87% level ($p = 0.124$), however, the *LAMI* coefficient was significant in the ECM model ($p = 0.059$). These results suggest that a 1% increase in national lane miles could increase *SVMT* by 4–5%. To understand this, recognize that the *LAMI* variable is based on national roadway data from FHWA and includes both rural and urban interstates and other roadways. In fact, as of 2012, about 71% of all the lane-miles in the US are rural, with 29% being classified as urban, and the share of urban lane-miles has grown from roughly 18% in 1980 to 29% in 2012 ([FHWA, 2013b](#)). We hypothesize that since *SVMT* occurs more locally with a significant amount of travel in growing urban areas, a disproportionate expansion of the roadway network in urban areas (compared to rural areas) may lead to *SVMT* increases, but would only increase *LAMI* modestly. This would lead to a high elasticity estimate for *LAMI*. We attempted to study this further by using urban lane miles as an explanatory variable in place of *LAMI*, but the coefficient on urban lane miles (although lower) was not statistically significant and the adjusted- R^2 of the model decreased. Better data are needed on roadway inventories and characteristics, and we reserve analysis of *SVMT* with respect to different road types for future research.

Another interesting result is the negative relationship between *GDP* and *SVMT*, yet a positive relationship between GDP_{t-1} and *SVMT*. Although more research is needed to better understand the roots of this relationship, it may be partly explained by recognizing that the single-unit truck sector is strongly influenced by construction and infrastructure investment (hence our significant, positive relationship between *SVMT* and *HOUC*) ([U.S. Census Bureau, 2004](#)). Since activity due to infrastructure investment may be lagged (i.e., construction investment commitments made today are carried out in future time periods), we may expect to see the kind of offsetting relationship across time periods as shown in our results.⁸ However, additional data that allow us to specify *SVMT* by vehicle type and activity type would allow us to better qualify these results.

Conclusion

In this paper we estimate the fuel price elasticity of single-unit truck travel, as measured in VMT. Since VMT is directly related to fuel consumption, our elasticities may be applied in the context of energy consumption in the single-unit segment

⁸ For example, a large *GDP* increase in one year may trigger infrastructure investment decisions in sectors that spur *SVMT* (e.g., construction) in the following year. If *GDP* growth rates decrease the following year, *SVMT* could still increase, leading to a negative coefficient on the GDP_t term, but a positive coefficient on the GDP_{t-1} term.

of the HDV sector under certain assumptions.⁹ Despite applying a variety of model specifications – including the use of first difference models and error correction models – we find that we cannot reject a null hypothesis that fuel price elasticities for single-unit truck VMT is zero. Our results are consistent with other recent work that shows fuel price inelasticity for combination trucks (Winebrake et al., 2015).

There may be good reasons why this inelasticity apparently exists in the market. For example, adjustments in other modifiable operational costs, such as labor or capital expenses, by trucking firms when fuel prices increases is one such explanation put forward in earlier work, along with other possible factors. For single-unit trucks, it may be that these vehicles operate in either (1) competitive carrier environments where carriers must absorb fuel price costs in order to maintain customers; or (2) non-competitive carrier environments where carriers can easily pass along fuel price increases without losing marketshare. More research on the effect of market structure on carrier behavior is needed to further understand the behavior we observe.

These results may help inform analyses related to policies aimed at improving the efficiency of HDVs. Those analyses look to evaluate the potential rebound effects that may occur due to efficiency improvements that effectively reduce fuel costs per mile for truck operators. One may use the elasticities in this paper as rebound proxies 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). In addition, cross-price elasticities between the trucking sector and other modes of transport (notably rail) could impact this rebound effect, although we expect inelastic cross-price elasticities in this case given the types of markets (more local and lower tonnage) within which single-unit trucks operate. Nevertheless, all these assumptions should be explored 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 single-unit truck sector (e.g. Dargay and Gately, 1997; Gately, 1993; Greene, 2012; Hymel and Small, 2015; Sentenac-Chemin, 2012; Winebrake et al., 2012).

Additional research and better data also are needed to estimate the rebound effect more directly using econometric approaches; for example, by measuring changes in HDV 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 time series MPG data are derived in part from aggregate fuel consumption and VMT data, and the use of these 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. For single-unit trucks, greater disaggregation of SVMT data (by commodity type, vehicle type, and roadway type, in particular) would be useful in determining the role of these factors on fuel price elasticities within this sector. Continued research in this area, with particular attention to the collection of disaggregated activity data before and after regulatory intervention, will be important in assessing the impact of future efficiency or environmental regulations affecting the truck sector.

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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.2015.05.003>.

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⁹ Fuel efficiency data could be used to translate VMT data into energy consumption data, but efficiency data are limited, as discussed below. Using fuel price elasticities of VMT as a proxy for fuel price elasticities of fuel consumption requires one to assume fuel price does not impact other variables that could also influence energy consumption.

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