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Diesel demand in the road freight sector in the UK: Estimates for different vehicle types

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Highlights

- UK diesel demand for light and heavy freight trucks modelled
- The transition from petrol to diesel controlled for in the model
- Both light and heavy duty sectors have income elasticity of around 0.8
- Rigid trucks have lower income elasticity than articulated trucks
- Light duty trucks are insensitive to price changes, heavy duty trucks respond by a small amount

Abstract

Demand elasticity for petrol or diesel is an important policy parameter, both from energy security and global warming perspective. Despite an abundance of literature on petrol demand, there are few studies on diesel demand, and even fewer on demand by different vehicle types. This paper aims to model diesel demand for different freight duty vehicle types (e.g. heavy vs. light goods vehicles and rigid vs. articulated trucks) in the UK. We argue that the switch to diesel from petrol engines in the light vehicles sectors could have biased earlier petrol or diesel demand elasticities in Europe, and show that it was indeed the case for the light goods vehicle sector. Results show that both light and heavy goods vehicles have similar income elasticities, although within the heavy duty sector, articulated trucks are more elastic than rigid trucks. Overall, heavy goods vehicles were responsive to fuel prices, but light goods vehicles were not. Within the heavy duty sector, rigid trucks showed statistically significant price elasticity, but articulated trucks did not respond to changes in fuel prices. Our results show that price-based policies to curb fuel consumption from the light or heavy goods vehicles are unlikely to be effective.

Keywords

Diesel fuel, freight transport, demand elasticity, econometric model, fuel switch

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1. Introduction

The use of diesel in light duty vehicles has attracted substantial attention in the UK recently. In an attempt to combat the adverse effects of climate change, various incentives were put forward in the UK during mid 1990s in order to reduce carbon emissions from the personal road transport sector. The quickest response to these incentives was a switch to diesel engines, which were more fuel and carbon efficient than similar petrol engines. Nearly two decades into these incentives, diesel cars and light goods vehicles (LGV) now have a larger market share in new vehicle sales in the UK. However, the resulting increases in NO_x[1] means that many UK cities now exceed the ambient NO_x standards. On the other hand, road freight transport - which is also dominated by diesel engines - has steadily increased its share of total road transport energy consumption (and carbon emissions) from 28.8% to 35.6% between 1970 and 2014. Since electrification is unlikely to be viable for decarbonising the heavy duty freight sector, liquid fuel are likely to remain in the fuel mix for a longer time. These two trends of dieselization of light duty fleet and increasing share of road freight in transport energy consumption is also observed in most European countries. These factors have led to a renewed interest in energy and, especially, diesel demand in the transport sector.

Energy demand for personal transport is one of the most widely researched area in energy economics because of the crucial role that energy plays in an economy. Elasticity for fuel demand, defined as the ratio of changes in fuel demand with respect to changes in price or income is an important parameter for policymakers. Income elasticities are especially useful to determine the future growth or slowdown in fuel consumption in response to rising income (GDP). On the other hand price elasticities are useful to understand the effects of carbon taxes, fuel taxes or such fiscal policies on consumption.

Traditionally, petrol or gasoline spark ignition engine was the dominant engine technology for personal vehicles, and as such studies on petrol demand abounds. In comparison, literature on demand for diesel, which had primarily been used for heavier duty freight vehicles, is much smaller. More importantly, the distinction between passenger vehicles and freight vehicles on the basis of petrol or diesel engines has been blurred in most European countries as a result of diesel's growing market share during the past two decades (Bonilla 2009). Since the two fuels no longer exclusively cover a specific activity (personal vs. freight travel), modelling total petrol or total diesel consumption has lost some of its previous usefulness in policy discussions. For example, transport

[1] Diesel engines emit more NOx than petrol engines.

and city planners may need to know the effect of taxation on diesel fuel on heavy-duty truck travel, but elasticities may be available only for total transport diesel, which would include cars and light commercial vehicles. Similarly petrol demand no longer represent fuel demand by all private cars, since a large share of private cars in Europe currently runs on diesel. As such, policymakers may be interested in knowing separate responses for fuel demand elasticities for freight and personal travel for these two major fuel types. However, there is a serious lack of understanding of the response of different vehicle sectors to fuel price or income changes, with only one credible study by Winebrake et al. (2015a), which is for articulated trucks in the US. Separate diesel demand models for light and heavy goods vehicles and rigid trucks or articulated trucks within the heavy duty fleet is not available in any study.

The dieselization of the UK and European light duty (cars and LGVs) vehicle fleet poses another methodological problem. The transition to diesel was primarily a result of innovations in diesel technology, rather than a response to price and income changes. This means that in any study, where this transition is not explicitly modelled, the income and price elasticities would be biased. Given nearly all recent studies on petrol or diesel demand use time-series data, which includes data during the last two decades, there is a possibility that the elasticity estimates in European countries, including the UK, were wrongly estimated.[2] Indeed, Dahl (2012) - in her extensive review of diesel demand studies - noted that income elasticity of diesel in Europe during 1990-2007 was 1.79, which was much higher than most other countries, clearly indicating the bias in the published elasticity estimates. Similarly, petrol demand has been falling in the UK and European countries since the late 1990s, which could also bias the price and income elasticity of petrol demand if the transition from petrol to diesel engines is not controlled for. Therefore there is a clear need for a method to derive demand elasticity after controlling for the fuel transition observed in most European countries.

Following this background, we make novel contribution to the literature in diesel demand by addressing these limitations in this research. Firstly, we model diesel demand for different types of road freight vehicles so that implications of price or income changes on diesel consumption in each of these vehicle fleet can be understood. To our knowledge, this is the first study - globally- to model price and income elasticities of diesel demand for light and heavy goods vehicles as well as rigid trucks and articulated trucks within the heavy duty fleet. Secondly, we make novel contributions to the modelling strategy in order to control for the transition of the fleet from predominantly petrol to predominantly diesel to correct the bias in the elasticity estimates in diesel demand that has afflicted the previous studies, especially in European countries. Thirdly, although the methodological

[2] Note that this will not be a problem in the US, since petrol to diesel transition did not occur there.

control for fuel transition is applied for diesel in LGV fleet in this study, the method can be applied for petrol or diesel demand in cars too, which makes our methods more widely applicable.

The paper is laid out as follows. Section 2 reviews the literature with a focus on diesel demand. Section 3 describes the data and provides some background on the evolution of diesel fuel demand in the freight sector in the UK. Section 4 describes the detail of the econometric model, while section 5 presents the detailed results for various vehicle segments and discusses the results. Section 6 draws conclusions.

2. Literature

The literature in diesel demand is much smaller as compared to that in petrol demand.[3] As such the methods used to model diesel demand are also more uniform. Table 1 summarises the features and findings of fifteen recent primary studies on diesel demand, all published since 2000. Each of these studies uses variations in aggregate diesel demand in temporal dimension and explains them with respect to fuel price, income and occasional other explanatory factors. Although cross-sectional information is used in conjunction with timeseries in some of these studies in a panel structure (e.g. Gonzales-Mareno et al. 2012), the demand data is still at an aggregate level, be it regional or national. Unlike in petrol demand models, using household level disaggregate data for modelling diesel consumption has not gained much purchase, presumably because of the historic use of diesel in heavy duty freight vehicles.

[Table 1 here]

Dahl (2012) reviewed 34 studies which modelled diesel demand and find that price and income elasticities were -0.16 and near 1 respectively. However, as mentioned earlier, Dahl (2012) find that the income elasticity in European countries were larger - around 1.78, which is an indication of our premise that elasticities could be biased if the petrol to diesel transition is not accounted for. In the UK, Ramli and Graham (2014) have recently modelled diesel demand, but their aggregate demand data contains diesel consumption from all heavy goods vehicles (HGV) and a share of light goods vehicles (LGV) and personal cars. Because of the rapid penetration of diesel engines in both passenger cars and LGVs during their observation period was not accounted for, it is likely that the income elasticity of 1.5 was also on the higher side. Interestingly, despite diesel's growing market share in Europe, there is a shortage of studies that model diesel demand in Europe.

[3] Extensive review of petrol demand is available in Wadud (2008), Dahl and Sterner (1991), or Basso and Oum (2007). In this section we focus on recent diesel demand work only.

Only a few recent studies attempted to control the transition from petrol to diesel while modelling elasticity of petrol or diesel demand. Pock (2010), although deals with petrol, is relevant here since the transition of European petrol car fleet to diesel has been explicitly modelled through using the size of petrol and diesel car fleet as additional explanatory variables. However his use of petrol consumption *per car* as the dependent variable misses a critical mechanism influencing petrol or diesel demand - the changes in car ownership *per capita* as a response to changes in income or fuel prices. It is likely that the low to statistically insignificant income elasticity for petrol demand is a direct outcome of the modelling strategy. Pock (2007) considers diesel demand, but like Ramli and Graham (2014) contains all automotive diesel, including cars and trucks, complicating modelling. Also the use of diesel *per car* as the dependent variable as in Pock (2010) has the same methodological problem. Among other studies of diesel demand in European countries, Liu (2014) and Pedregal et al. (2009) did not control for the diesel switch in Europe and Spain respectively, while Gonzalez- Mareno et al. (2012) found statistically insignificant income elasticities for Spain, possibly because of the use of diesel vehicle stock in the explanatory factors. Therefore a clear need exists for diesel demand models which can correctly control for the transition from petrol to diesel. This research aims to address this gap through modelling diesel demand in the LGV sector in the UK, which has gone through a similar transition from petrol to diesel.

In terms of modelling diesel demand for different vehicle types, Belhaj (2002) focused on light and heavy duty vehicles in Morocco. However, his finding of zero income elasticity of diesel demand for both the vehicle types is unrealistic. A closer inspection shows that their model includes diesel vehicle stock as a dependent variable, which precludes the possibility that vehicle stock would itself increase as a response to income or GDP increases. Also, the likely high correlation between vehicle stock and income or GDP made the income elasticity statistically insignificant. Recently Winebrake et al. (2015a) studied articulated trucks in the US and find that diesel price elasticity changed from -0.36 during pre-deregulation era to nearly zero now. This model does not have income or GDP as an explanatory factor, so income elasticity is not available. Therefore, there is still a lack of a study that generates price and income elasticities of diesel demand for different types of freight vehicles. As such, the second objective of this study is to separately model diesel demand for LGVs and HGVs in the UK, and also to model the price and income elasticities for rigid and articulated trucks within the HGV sector.

3. Data

The diesel demand data comes from the Transport Data Tables of the Energy Consumption in the UK series, published by the Department for Energy and Climate Change (DECC). The fuel consumption data is available for cars, light goods vehicles (LGV) and heavy goods vehicles (HGV), differentiated by petrol and diesel. Fig. 1 presents the total road diesel and petrol consumed in the UK from 1970 to 2013. It is clear that petrol demand grew until 1990 but then started decreasing due to the penetration of diesel engines in the personal vehicle stock. On the other hand, total diesel demand continues to grow to date. Fig. 2 disaggregates total road fuel consumption in the UK by various vehicle and fuel types, while Fig. 3 focuses only on diesel consumption from cars, buses, LGVs and HGVs. As can be seen, diesel consumption in passenger cars and LGVs were negligible until late eighties, when it started picking up, possibly due to the introduction of turbo diesel engines in 1988. Although, both the passenger cars and LGV segment were dominated by petrol engines earlier, the HGV segment (articulated and rigid trucks) was always almost entirely diesel fleet due to the suitability of diesel engines to carry heavy loads.

[Fig. 1 here]

[Fig. 2 here]

[Fig. 3 here]

Per capita real GDP and disposable income data is collected from the Office for National Statistics (ONS). Diesel and petrol price timeseries data was collected from DECC, which were deflated using the consumer price index from ONS. The share of manufacturing to UK's GDP over the years is collected from the National Income Account of ONS. Real GDP per capita, real diesel price and shares of manufacturing and service sector to UK's GDP are presented in Fig. 4.

[Fig. 4 here]

4. Model specification

4.1 Basic functional form

The basic functional specification for modelling transport fuel demand using timeseries data is the Cobb-Douglas specification, where the elasticity of demand with respect to the relevant variables are assumed constant. Although there are examples where elasticities may not remain constant (e.g. income elasticity reduces at higher income) [4], this is still the most widely used formulation in transport energy demand literature. We follow the same approach where the basic factors affecting diesel demand are income and price of diesel. Depending upon different vehicle classes we also

[4] Note that such gradual changes in elasticities can still be modelled using the constant elasticity formulation by interacting variables.

allow other variables (continuous or binary dummy or their interactions) to control for the impacts of various other exogenous policy or structural changes. Thus the basic specification is:

$$lnDIS_{it} = \alpha_i + \beta_i lnINC_t + \gamma_i lnDPR_t + \sum \delta_{ij} X_{jt} + \varepsilon_{it} \quad (1)$$

where, DIS = Diesel consumption per capita by vehicle type i at time t

INC = Income or GDP per capita at time t

DPR = Diesel price at time t

X_j = Other exogenous factors 1 .. j for vehicle type i at time t

Time series data has the risk of being non-stationary. Regression involving non-stationary variables can be spurious unless there is a long term stable relationship between the variables, in which case the variables are said to be cointegrated. It is therefore important to test for cointegration among the variables before inference can be made about the parameters estimated from the regression. Accordingly, during the last decade the Engle-Granger's (1987) two step method for cointegration has been extensively applied to model petrol and diesel demand (e.g. Ramli and Graham 2014, Wadud et al. 2009). Wadud et al. (2009) noted that the previous petrol demand models were likely still valid, despite not explicitly testing for cointegration since petrol demand, income and petrol prices more often than not show a cointegrating relationship, unless there is a structural break such as the sudden oil price hikes in the seventies (Wadud et al. 2009).

If cointegration does not hold with non-stationary data, it could be necessary to perform the regression with differenced variables, which would make the variables stationary as long as the original variables were integrated of order one. Given our timeseries data indeed contain the price hikes of the 1970s it is highly likely that the variables may not cointegrate.[5] In such a case, the estimating equation in the differenced form will be:

$$\Delta lnDIS_{it} = \beta_i \Delta lnINC_t + \gamma_i \Delta lnDPR_t + \sum \delta_{ij} \Delta X_{jt} + \varepsilon_{it} + \varepsilon_{i,t-1} \quad (2)$$

Independently, Eq. 2 defines the relationship between changes in diesel consumption and changes in the explanatory factors. Lags of the differenced dependent variable and independent variables can also be included, if necessary, and often an autoregressive formulation suffices:

$$\Delta lnDIS_{it} = \sum \mu_{ik} \Delta lnDIS_{i,t-k} + \beta_i \Delta lnINC_t + \gamma_i \Delta lnDPR_t + \sum \delta_{ij} \Delta X_{jt} + \varepsilon'_{it} \quad (3)$$

[5] e.g., Wadud et al. (2009) find that pre-seventies petrol demand, income and petrol prices in the US do not cointegrate, although post eighties data show cointegration.

where k is chosen such that the errors are serially uncorrelated, normally distributed and white noise. This differenced formulation is similar to the recent work of Winebrake et al. (2015a). The additional explanatory factors are different for different vehicle types because the exogenous policies or events driving diesel demand may or may not affect all vehicle types. For example, relaxation of maximum truck weight from 32 tonnes in 1983 affected the HGVs, but not the LGVs. Specific formulations for different vehicle types are discussed below.

4.2 HGV

As Fig. 2 shows, diesel engines were the dominant engine type for HGVs even at the start of the timeseries. However, over the last 40 years, the nature of heavy goods transport have changed substantially. In the seventies, bulk energy goods like coal were a substantial part of total tons transported while manufacturing's contribution to the UK economy was around 36%, which has fallen to around 10% at the end of our observation period (Fig. 4). Service sector has grown rapidly, while the supply chain and logistics have changed substantially with spatial consolidation, just-in-time delivery etc (McKinnon 1989) affecting freight activity pattern and fuel consumption. All of these changes were gradual and it is difficult to identify one specific point in time as the start of the change.

In addition to the gradual changes, specific events such as changes in regulation can also affect the activities in the HGV sector and thus fuel demand. These external regulatory changes include the permission of 38 tonne lorries on UK roads in 1983, deregulation of international road haulage in the European Union and opening of the channel tunnel in 1993, revival of rail as a competitive freight mode due to rail deregulation in 1997 (McKinnon 1989, 2007).

GDP is a better measure to explain freight activity in a country as opposed to disposable income. Therefore GDP is used to explain diesel demand in the HGVs. We include logarithm of the share of manufacturing in GDP in order to control for the changing structure of economy and its effects on heavy goods transport. The policy induced changes in 1983, 1993 and 1997 can be modelled in two different ways. One way is to add dummy variables to separate pre- and post-events effects. For example, in order to understand the effects of larger lorries on increasing road freight competitiveness and diesel consumption, the corresponding dummy variable shall have values of 1 for post 1983 years and 0 for pre 1983 years in the differenced model specification (Eqs. 2-3). In essence it translates into a time trend starting in 1983 for the model specification with the variables in level (i.e. Eq. 1). The other option is to use an interaction between the dummy variable and GDP in Eq. 1. This approach assumes that the relationship between diesel demand and GDP has changed since 1983, which possibly is a better approach to model the 'decoupling' of diesel demand for HGVs with national GDP, as discussed by McKinnon (2007) and Sorrell et al.(2012). During the model selection phase we test both these approaches for HGVs. Given the collinearity of these policy dummy or dummy-GDP interactions with other explanatory factors, statistical tests are used to include or exclude them from the final model. The explanatory factors remain the same for separate estimation of diesel demand for articulated and rigid trucks, too.

4.3 LGV

The LGV sector is different from the HGVs because of the co-existence of both petrol and diesel engines in this segment. Around 14% of energy consumed in the LGV fleet in 1970 was diesel, while in 2013 the diesel share rose to 95% (Fig. 3). At the same time, total LGV fuel demand increased by about two-folds, which means diesel consumption in the LGV fleet increased nearly 18 times. Clearly all of this increase in diesel consumption cannot be attributed to a GDP or fuel price effect, and technology had a major role to play in the transition from petrol to diesel in the LGV sector. For example, the LGV diesel consumption showed a clear deviation from previous trend in late 1980s, with no apparent policy push, and this was likely due to the introduction of turbo diesel engines which allowed the smaller segment of LGVs to switch from petrol to diesel, too.

While it is possible to model diesel demand in LGVs using the basic modelling framework in Eq. 1 (if cointegration holds) or Eqs. 2-3 (if there is no cointegration), this would likely bias the income elasticities upward, as the rapid growth in diesel demand since late eighties was primarily a result of technology substitution, rather than a purely income effect. It is therefore important to control for this transition, which we approach in two ways. Our first approach is to use a dynamic autoregressive model, where the lagged value(s) of the dependent variable also enters as an explanatory factor: this implies inertia in the changes in consumption. A time trend is also included from 1988 in Eq. 1, which becomes a binary variable with a value of unity for post 1988 years in Eqs. 2-3.

The second approach to modelling the transition is to use further time variables. In this approach, a time trend from 1988, as just mentioned above, is included. This, however, ignores the issue of self selection and its effect on diesel consumption. Since diesel engines are more expensive but are cheaper to run because of their higher fuel efficiency, LGVs that accrue a high mileage and high fuel consumption are expected to reach the breakeven point quicker and thus are likely to switch from petrol to diesel earlier. This would mean that at a later stage, even the same number of transition from petrol to diesel would possibly result in proportionally lower increase in diesel consumption as the later vehicles would most likely have had a lower mileage. We model this potential effect of self-selection on diesel consumption by adding a quadratic time trend in the model specification.[6] The quadratic term also captures the effects of better fuel economy of the vehicles over time and potential slowing down of the switch from petrol to diesel.

We also test the effects of including the share of service sector to the GDP (SVC) as an explanatory factor, in order to control for the changes in the structure of the economy, as we did earlier for HGVs. Similarly, the inclusion of the ratio of petrol to diesel prices (RAT), which could have an effect on the rate of transition from petrol to diesel, is also tested.

5. Results and Discussions

5.1 Stationarity, non-stationarity and cointegration

The first step in estimating models with timeseries data is pre-testing the continuous variables for their stationarity properties. Dickey Fuller augmented unit root test shows that $lnDIS$, $lnGDP$, $lnINC$, $lnDPR$, $lnMAN$, $lnSVC$, are all non-stationary. The first differences of these variables are all stationary, indicating the variables are integrated to order one (Table 2). The residuals from the OLS estimation between diesel consumption per capita, GDP per capita and diesel price (all in logarithms) can be tested for the absence of a unit root in order to establish cointegration between these variables. However, preliminary tests showed that there exist no long-run relationship among these three variables, either for HGVs or LGVs (Table 2). This is not surprising given our temporal dataset includes several factors such as the oil price hikes, introduction of turbo diesel engines to the fleet, changes in government policies, structure of the economy and supply chain and logistics practices which could have affected the long-run relationship. Given the non-stationarity of the variables in level and the lack of cointegration, the rest of the section discusses the results of the differenced models only.

[Table 2 here]

5.2 HGV

Table 3 presents the parameter estimates for two models for diesel consumption in HGVs. Model H1 includes the dummy variables to capture the effects of policy changes in 1983, 1993 and 1997, while Model H2 uses the interaction of dummies with $lnGDP$. Statistical tests employed for model diagnostics are the Portmanteau test for white noise, Shapiro-Wilk test for normality, Breusch-

[6] Another approach to capturing self-selection using car stock is described in Pock (2010), but we do not have data on LGV diesel vehicle stock.

Godfrey test for autocorrelation and Lagrange Multiplier test for ARCH effects. The OLS standard errors are also modified using Huber-White Sandwich estimators to correct for any minor variations from standard OLS assumptions.[7]

[Table 3 here]

Given the high correlation between dummies in 1993 and 1997, only one of them could be included in the final models. The 1993 dummy or interaction produced better model fits, so in our final models this dummy captures the effects of both the opening of channel tunnel and liberalization to allow European freight hauliers in 1993 and deregulation of the rail sector in 1997.

The income elasticity of diesel consumption for HGVs ranges from 0.8 to 0.94 - statistically significant at 99% confidence level for both models. Price elasticity lies between 0.12 and 0.15 (negative). However, price elasticities are statistically insignificant at a typical 95% confidence level, but they are significant at 90%, making a strong inference difficult. Winebrake et al. (2015a, 2015b) clearly found fuel demand from articulated trucks and travel activity of rigid trucks in the USA to be statistically not different from zero, yet we believe rail has emerged as a reasonable substitute to HGVs in the UK, making HGV activities and thus fuel consumption somewhat responsive to fuel costs.

Model H2 shows that the relationship between GDP and diesel consumption in the HGVs may have changed around 1983, but the opening of channel tunnel, competition from the European hauliers and deregulation of rail did not have any statistically significant effect on the relationship between GDP and diesel consumption. Although both the models pass all diagnostic tests, Model H1 perform substantially better than Model H2 in terms of Adjusted R^2, AIC or BIC.

Model H1 shows that since 1983 diesel demand started increasing more than its typical GDP-price relationship would suggest. The lorry weight limits were increased from 32 tonnes to 38 tonnes in 1983. Although a positive estimate for the 1983 dummy might appear counter-intuitive since fuel consumption per ton-mile actually decreases in heavier lorries, the lower costs may have made freight transport by road more attractive and brought about a larger demand for road freight transport which more than compensated any fuel gains per vehicle. It is also likely that the dummy variable for 1983 represents the effects of several developments around that time which spurred a growth in the HGV sector and thus fuel consumption in this sector.

The dummy for 1993 has a negative value. This indicates that the combined effects of opening of the channel tunnel, entry of European freighters to UK market and increased competition from rail since

[7] Although the errors in Eq. 2 are moving average, the moving average component was found statistically insignificant when tested.

its deregulation had a negative effect on diesel consumption in HGVs. The opening of channel tunnel in 1993 and deregulation of British Rail in 1997 improved the attractiveness of rail as a freight mode for both domestic and international freight haulage and it is expected that their effects would be negative on the road freight activities and thus diesel consumption in the HGVs. Although the European Union wide deregulation in international road haulage was expected to lower freight rates, UK road freight sector had already been deregulated for around 20 years and thus was possibly already competitive with European haulers. Nonetheless, continental freighters increased their share of ton-miles in UK market in recent years, yet that was possibly not large enough to overcome the effects of increase in rail's modal share from 1993, resulting in a negative parameter estimate for this dummy variable.

5.3 Rigid and Articulated Trucks

We are also interested in comparing the responses of rigid and articulated trucks within the HGV sector. Therefore, we run our HGV Model H1 for both these vehicle types. The parameter estimates for these models are presented in Table 4. All the explanatory factors are the same as before, with the addition of a dummy for year 1989 in order to account for a large outlier in the residuals. As before, both of these models pass the autocorrelation, ARCH, normality and white noise tests for errors.

[Table 4 here]

These estimates show that diesel consumption in articulated trucks had a larger income elasticity as compared to rigid trucks. Freight activities (vehicle-miles or tonne-mile) in articulate trucks grew more rapidly than rigid trucks during the last three decades, so this result is hardly surprising. Diesel consumption in rigid trucks are also positively influenced by an increase in the share of manufacturing in GDP. For articulated trucks, this parameter estimate is similar, but significant only at 85% confidence level. As such a strong inference cannot be made, but it is more likely than not that manufacturing share of GDP has an influence on freight activity and fuel consumption in articulated trucks, too. The effects of the two dummies representing external changes affecting the trends in 1983 and 1993 are similar to the previous results for HGVs: relaxation of weight restrictions of 1983 increased diesel consumption in both rigid and articulated trucks, while the combined effects of the opening of channel tunnel and deregulation of UK rail and EU-wide road freight sector was a reduction in diesel consumption in both truck types. Although the relaxation of weight restrictions did not affect the rigid trucks directly, our results indicate that the policy possibly brought about a wider-ranging modal switch to road sector, which benefited the rigid trucks as well, increasing diesel consumption in this sector, too.

The price elasticity estimates are different for rigid and articulated trucks, though. Diesel consumption in rigid trucks have a price elasticity of -0.15, which is small but statistically significant at 95% confidence level. For articulated trucks, price elasticity has the correct sign, but is clearly statistically not different from zero. While this explains our somewhat weak inference for price elasticity for the entire HGV sector above (i.e. statistically significant at 90%, but not significant at 95%), the econometric model cannot explain why the price elasticities are different. In Table 5 we presents the share of fuel costs in total operating costs of different types of rigid and articulated trucks. It is clear that fuel is a larger share of operating costs for articulated trucks, which should have made the articulated trucks more cost sensitive. However, Table 5 also reveals that the rigid truck sector shows a large variation (6.9p-31.6p) in per-ton mile transport costs, while for articulated trucks and heavier rigid trucks the range is much narrower, between 4.1p-6.9p/ton-mile. This indicates that the potential for substitution within or away from articulated trucks is likely much limited when fuel price changes. Given the large share of fuel costs, articulated trucks often are the most fuel-efficient ones (on a per ton-mile basis), limiting opportunities to improve fuel consumption through fleet renewal in response to higher prices. These factors likely make articulated trucks less responsive to fuel price changes.

[Table 5 here]

5.4 LGV

Table 6 presents the parameter estimates for the two models for diesel consumption in the LGVs. Model L1 is the autoregressive one, where the lagged dependent variable is included as a regressor, while Model L2 uses a quadratic trend to control for the transition from petrol to diesel engines in the LGV sector. Tests for inclusion of a variable to control for the growth of the service sector in UK economy (SVC) were rejected for both the models by likelihood ratio test. Similarly, ratio of petrol to diesel prices (RAT) were also excluded from both the final specifications. Also, an outlier for 1989 was accounted for by adding a dummy variable for that specific year only.

[Table 6 here]

Income elasticities for diesel demand in LGVs range from 0.83 to 0.95, which is quite similar to those of HGVs. There was a clear trend of increased consumption from 1988 as evidenced by the statistically significant positive parameter estimates for $\Delta TIME88$ in both models. As mentioned earlier, this is likely due to the introduction of better diesel engine technologies. Model L1 shows that the changes in diesel consumption in previous period has statistically significant effect on the changes in consumption in the current period, thus somewhat capturing the inertia and petrol to diesel transition effects. The negative parameter on the quadratic time variable ($\Delta TIME88SQ$) indeed confirms that diesel consumption growth rate had slowed down in recent years. This represents the combined effect of self selection (i.e. LGVs that were converted later usually runs less), improved fuel economy and a slower rate of switch from petrol to diesel. A comparison of Adjusted R^2, AIC and BIC statistics reveals that Model L2 fits the data better than Model L1.

The price elasticities of diesel demand in LGVs are statistically insignificant in both models. This finding requires some explanation. LGVs are defined as goods vehicles with a gross weight less than 3.5 tonnes, while anything above 3.5 tonnes are HGVs. However, LGVs not only include typical goods vehicles (i.e. small trucks), but also include different types of vans (box van, car derived van, light van, luton van, panel van, etc.), pick-ups, livestock carriers, concrete mixers, airport support units, mobile plants, motor homes, refuse trucks, tippers, tractors etc (Allen and Browne 2008). Given the wide variety of services and tasks performed by these vehicles, the good-transporting function is often not important for a large share of LGVs. Indeed, Allen and Browne (2008) find that only 22% of trips and 30% of vehicle-miles made by LGVs in the UK were for commercial freight carrying activities during 2002-2003. This would mean that the traditional freight business model for HGVs where fuel costs are an important cost element in the process may not be applicable for LGVs where other cost concerns and service delivery may have priority over fuel consumption. Table 4 earlier shows that the LGVs have the lowest share of fuel costs in its operating costs among all freight vehicles, potentially making it less sensitive to fuel prices. In addition, opportunities for substituting the tasks or services between different types of LGVs is also limited. All of these factors suggest that it is indeed possible for price elasticity of diesel to be near zero in the LGV sector.

In order to compare our results with a model that does not control for the growth in diesel LGVs, we run a third model, Model L3, which is nested in Model L2 and does not contain the linear or quadratic time trend. An appropriate specification which passes all the statistical tests was difficult, so we use robust standard errors for inference. The income elasticity for this model is 1.78, which is substantially higher than the original income elasticity 0.83, and the price elasticity becomes unexpectedly positive and significant, supporting our premise that the parameters can be biased if the transition from petrol is not controlled for, as was the case for petrol and diesel demand models in many previous studies in Europe.

Conclusions

In this paper we set out to determine the elasticities of diesel demand in the UK for different freight vehicle sectors. We find that diesel demand in both LGVs and HGVs has an income elasticity near 0.8. - which falls right at the demarcation boundary between weak decoupling and expansive coupling (Tapio 2005). The income elasticity is slightly lower in rigid trucks, around 0.56, indicating a weak decoupling effect while for articulated trucks its nearly twice as much. This reflects the rapid growth in articulated truck activities within the of heavy duty freight sector. Diesel demand in the road freight sector responds less to the explanatory factors since 1993, indicating some form of decoupling, most likely due to an increased competition from rail after the opening of the channel tunnel and rail deregulation.

One of the initial premise of this work was that the income elasticities and other parameter estimates could be biased if the rapid petrol to diesel switch, observed in many European countries in the car and LGV sector in the past two decades, is not controlled for in a demand model. For the LGV sector in the UK, we do find evidence that income elasticity in an uncontrolled model can be nearly twice as high as in the correct model, and this finding is likely to hold in other European countries, too. Although we do not focus on cars in this study, similar bias is expected for income elasticity of petrol and diesel demand for cars in most European countries and other countries which experienced such a transition from petrol to diesel.

Diesel consumption in freight vehicles overall is quite inelastic. Diesel demand in articulated trucks and LGVs do not respond to changes in diesel prices at all, which indicates the lack of substitutes available in these sectors. Demand in rigid trucks does decrease due to fuel price increases, but the response is still inelastic and small - around 0.15. These findings agree with Dahl's (2012) summary of diesel demands studies or recent work of Winebrake et al. (2015) in the US.

The findings have some important policy and research implications. First, the existing elasticities in literature should not be used for long term forecasting of petrol and diesel demand in those European or other countries, where such a fuel transition took place as the diesel forecasts will most likely be overestimated. Second, in future studies on fuel demand, especially in Europe, the switch from petrol to diesel must be included to uncover true elasticities - for either of petrol or diesel. Third, although there is some weak evidence of potential decoupling since mid-1990s, fuel consumption in the HGV and LGV sector still responds quite strongly to changes in the GDP or economic activities. Finally, since price elasticities are near-zero, pricing may not be an effective way to control fuel consumption and carbon emission in the freight sector and other policy alternatives need to be investigated.

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Figures

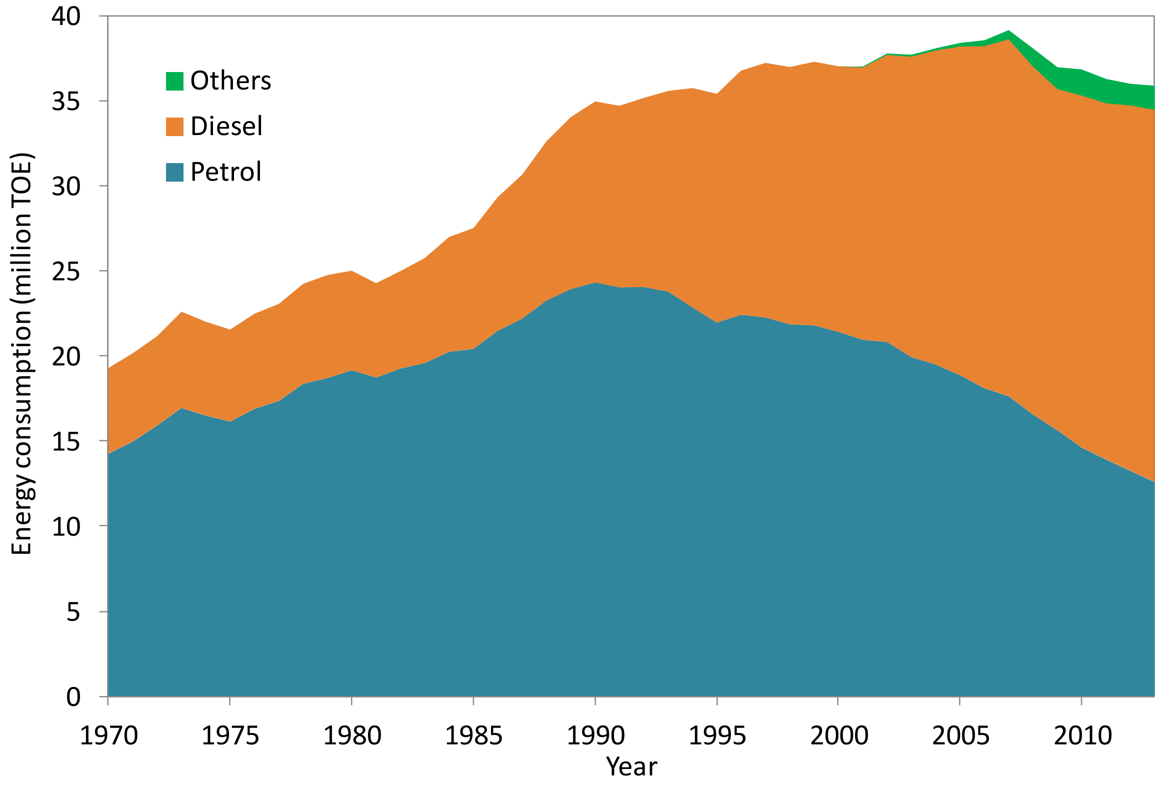

Fig. 1 Energy consumption in the transport sector in the UK

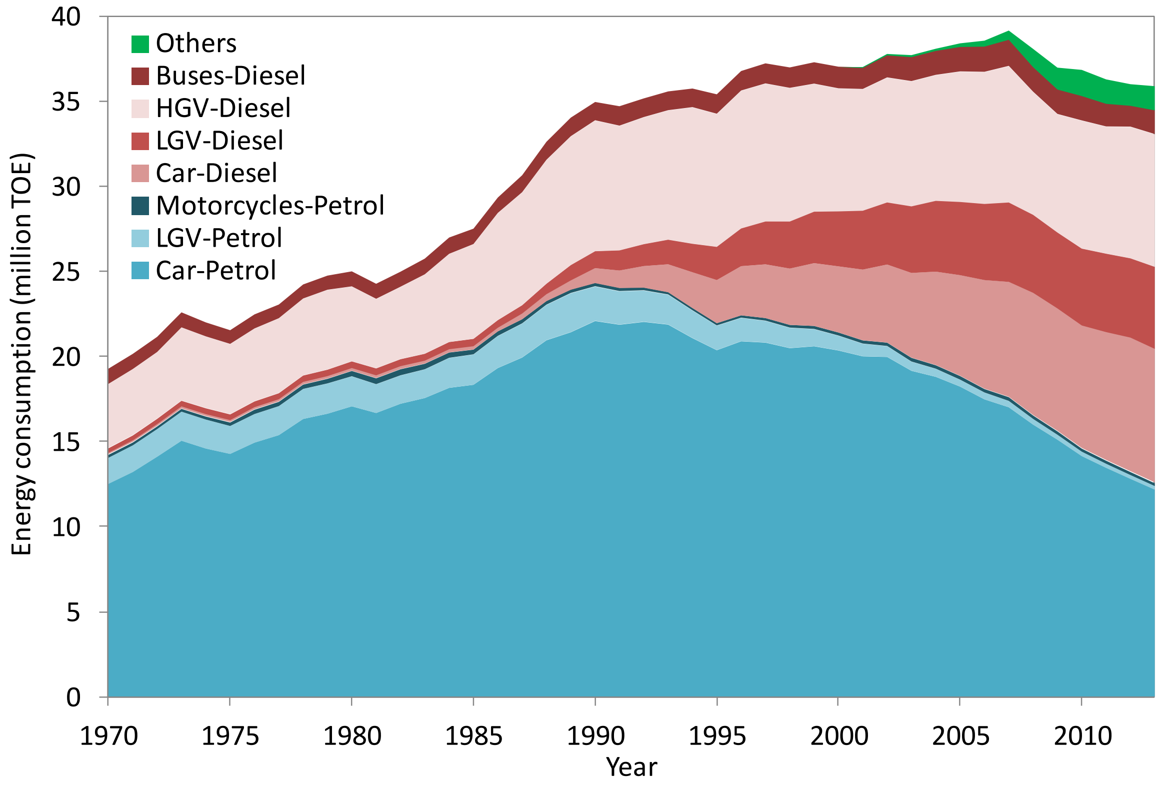

Fig. 2 Energy consumption by vehicle and fuel type

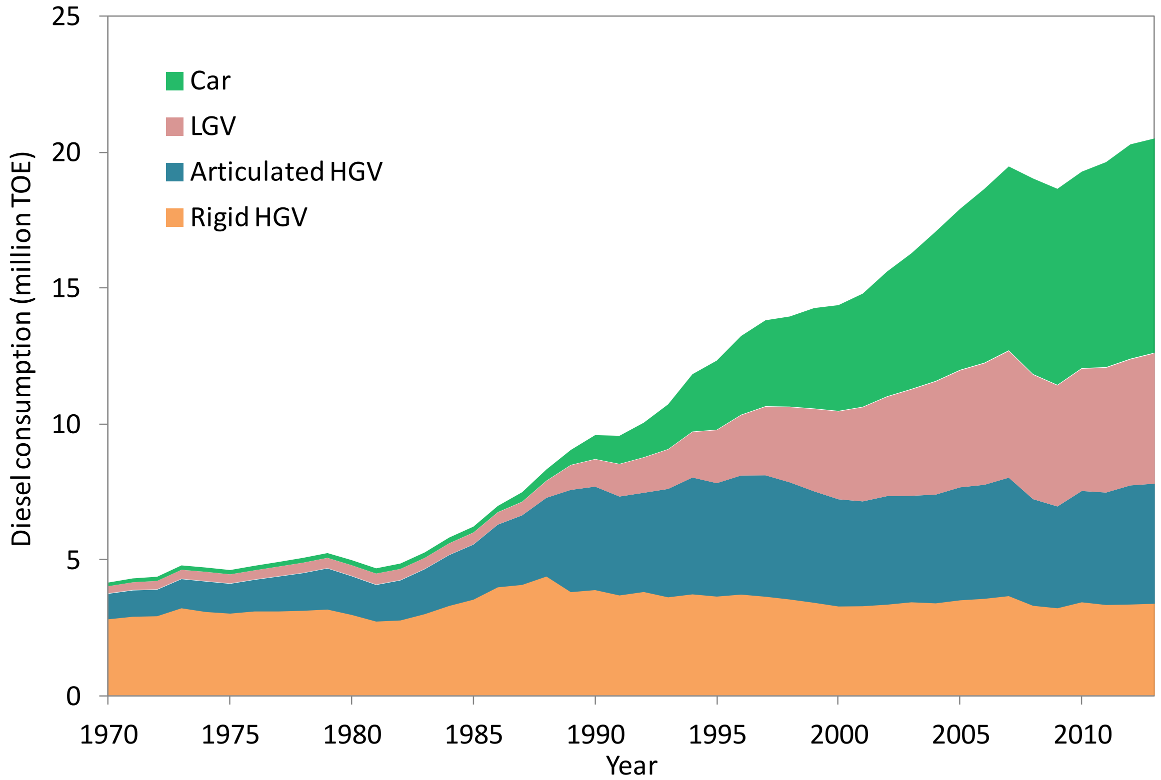

Fig. 3 Diesel consumption by vehicle type

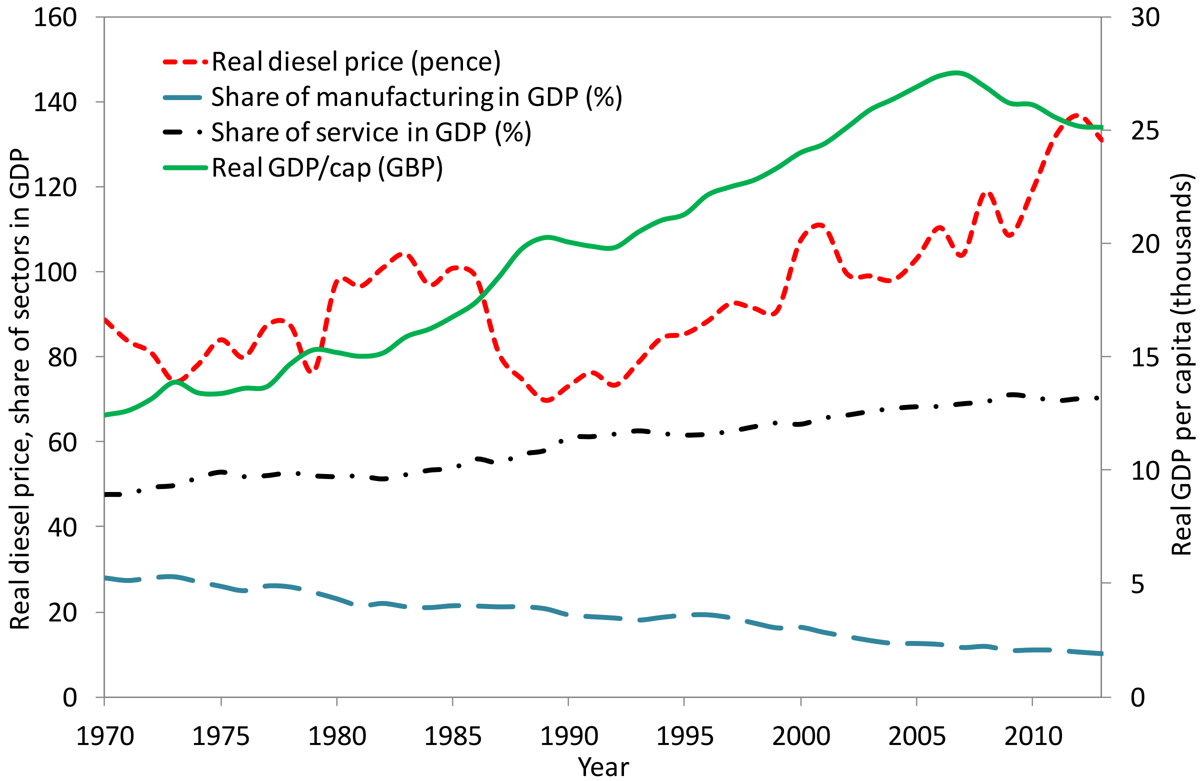

Fig. 4 Real GDP, real price of diesel and share of different sectors in the GDP

Tables

Table 1. Summary of primary studies of Diesel demand since 2000

Study	Location	Data	Dependent variable	Explanatory factors	Method	Income elasticity Short/long run	Price elasticity Short/long run
Dahl & Kurtubi (2001)	Indonesia	Annual, 1970-1995	Road diesel pc	Diesel price, GDP pc	Error-correction & cointegration	2.15/2.16	Insig/-0.67
Belhaj (2002)	Morocco	Annual, 1970-1996, vehicle type	Road diesel pc	Diesel price, GDP pc, vehicle stock pc, trend	Partial adjustment	Insig.	-0.18 for light & heavy vehicles
Liu (2004)	OECD	23 countries, Annual, 1978-1999	Road diesel pc	Diesel price, GDP pc	Dynamic panel	0.43/1.21	-0.1/-0.27
Polemis (2006)	Greece	Annual 1978-2003	Road diesel pc	Diesel & petrol price, GDP pc, diesel stock pc	Cointegration	0.42/1.18	-0.07/Insig.
De Vita et al. (2006)	Namibia	Quarterly, 1980-2002	Total diesel	Diesel price, GDP, temperature	Cointegration	2.08	Insig.
Pock (2007)	EU	14 countries, annual, 1990-2004	Road diesel per diesel car	Diesel price, GDP pc, petrol & diesel car per driver	Dynamic panel	0.63/1.44	-0.13/-0.29
Pedregal et al. (2009)	Spain	Monthly, 1984-2006	Road diesel	Gasoline to diesel price ratio, GDP, trend	Unobserved component	Insig.	Insig.
Bhattacharyya & Blake (2009)	Middle East & North Africa	7 countries, annual 1982-2005	Diesel pc	Diesel price, GDP pc	Partial adjustment, individual countries	Mix of insig., +ve & -ve estimates	Mix of insig., +ve & -ve estimates
Lootty et al. (2009)	Brazil	Annual, 1970-2005	Spending on diesel	Price of all fuels, total spending on fuels	Almost ideal demand system	-	-0.63
Iwayemi et al. (2010)	Nigeria	Annual, 1977-2006	Road diesel	Diesel price, GDP	Vector cointegration	Insig.	Insig.
Suleiman & Muhammad (2012)	Afircan OPEC countries	Annual, 1980-2008	Diesel pc	Diesel price, GDP pc	Cointegration, individual countries	Insig. to 1.0	Insig. to -0.4

Study	Location	Data	Dependent variable	Explanatory factors	Method	Income elasticity Short/long run	Price elasticity Short/long run
Gonzalez-Mareno et al. (2012)	Spain, regional	16 regions, annual 1998-2006	Road diesel pc	Diesel & petrol price, GDP pc, diesel and petrol vehicle stock pc, congestion	Dynamic panel	Insig.	Insig.
Ramli & Graham (2014)	UK	Annual, 1980-2009	Road diesel pc	Diesel price, income pc	Cointegration	0.71/1.5	-0.11/-0.3
Barla et al. (2014)	Canada	Annual, 1986-2008	Road diesel pc	Diesel price, GDP pc, share of primary sector	Cointegration, partial adjustment	Insig./0.91	-0.43/-0.8
Winebrake et al. (2015a)	US articulated truck fleet	Annual, 1970-2012	Diesel in art. trucks	Diesel price, international trade	First difference	n/a	-0.36 to insig.

pc= per capita

Table 2. Unit root tests

Variable tested	DF-GLS statistic (5% critical value)	Remarks
$lnDIS_{HGV}$	-1.233 (-3.283)	Non-stationary
$lnDIS_{LGV}$	-1.572 (-3.283)	Non-stationary
$lnGDP$	- 1.546 (-3.283)	Non-stationary
$lnRDP$	-1.488 (-3.283)	Non-stationary
$lnMAN$	- 1.413 (-3.283)	Non-stationary
$lnSVC$	- 2.303 (-3.283)	Non-stationary
$lnRAT$	-2.542 (-3.283)	Non-Stationary
$\Delta lnDIS_{HGV}$	-3.404 (-3.293)	Stationary
$\Delta lnDIS_{LGV}$	-2.384 (-2.329)	Stationary
$\Delta lnGDP$	-3.435 (-3.293)	Stationary
$\Delta lnRDP$	-4.511 (-3.293)	Stationary
$\Delta lnMAN$	-3.756 (-3.293)	Stationary
$\Delta lnSVC$	-3.373 (-3.293)	Stationary
$\Delta lnRAT$	-6.449 (-3.293)	Stationary
Residual of the regression: $lnDIS_{HGV}=\alpha lnGDP+\beta lnRDP$	-2.087 (-3.283)	No cointegration
Residual of the regression: $lnDIS_{LGV}=\alpha lnGDP+\beta lnRDP$	-1.562 (-3.283)	No cointegration

Table 3. Parameter estimates for diesel consumption in HGVs

Variable	Description	Model H1	Model H2
$\Delta lnGDP$	GDP per capita (in log, differenced)	0.800 (3.56)***	0.938 (4.43)***
$\Delta lnDPR$	Diesel price (in log, differenced)	-0.120 (-1.85)*	-0.148 (-1.99)*
$\Delta lnMAN$	Share of manufacturing to GDP (in log, differenced)	0.342 (2.12)**	0.305 (2.52)***
$DTR83$	Dummy =1 for post 1983 years	0.035 (2.25)**	-
$DTR93$	Dummy =1 for post 1993 years	-0.034 (-2.18)**	-
$\Delta DTR83\times lnGDP$	Interaction between $DTR83$ & $lnGDP$ (differenced)	-	0.007 (6.09)***
$\Delta DTR93\times lnGDP$	Interaction between $DTR93$ & $lnGDP$ (differenced)	-	0.0003 (0.08)
Diagnostics			
Adjusted R^2		0.493	0.438
AIC		-157.72	-153.27
BIC		-148.91	-144.47
Autocorrelation	Breusch-Godfrey's LM test	0.005 (p=0.94)	0.149 (p=0.70)
ARCH effects	LM test	1.03 (p=0.31)	0.570 (p=0.45)
Normality	Shapiro Wilk test	-0.25 (p=0.60)	0.361 p=0.36)
White noise	Portmanteau test	13.69 (p=0.80)	15.87 (p=0.67)

Statistically significant at *** 99%, ** 95%, * 90%

Table 4. Parameter estimates for diesel consumption in rigid and articulated trucks

Variable	Description	Rigid	Articulated
$\Delta lnGDP$	GDP per capita (in log, differenced)	0.563 (2.45)**	1.170 (4.06)***
$\Delta lnDPR$	Diesel price (in log, differenced)	-0.156 (-2.17)**	-0.081 (-1.01)
$\Delta lnMAN$	Share of manufacturing to GDP (in log, differenced)	0.306 (1.91)**	0.301 (1.45)$^{\#}$
$DTR83$	Dummy = 1 for post 1983 years	0.034 (1.93)*	0.041 (2.36)**
$DTR93$	Dummy = 1 for post 1993 years	-0.039 (-2.23)**	-0.039 (-2.19)**
$D89$	Dummy = 1 for 1989	-0.194 (-11.24)***	0.192 (13.77)***
Diagnostics			
Adjusted R^2		0.512	0.586
AIC		-156.79	-131.20
BIC		-146.23	-120.63
Autocorrelation	Breusch-Godfrey's LM test	0.670 (p=0.41)	1.163 (p=0.28)
ARCH effects	LM test	0.725 (p=0.39)	3.010 (p=0.08)
Normality	Shapiro Wilk test	0.392 (p=0.35)	-0.147 (p=0.55)
White noise	Portmanteau test	13.98 (p=0.78)	13.31 (p=0.82)

Statistically significant at *** 99%, ** 95%, * 90%, $^{\#}$ 85%

Table 5. Share of fuel cost and total operating costs of different types of goods vehicles

Weight	Truck type	Share of fuel cost in operating costs (%)		Operating costs (p/ton-mile)*
		RHA (2014)	FTA (2015)	RHA (2014)
<3.5T	LGV		13$^{\#}$	
3.5T	Rigid HGV	17	-	31.6
7.5T	Rigid HGV	22	21	18.3
13T	Rigid HGV	23	22	12.1
18T	Rigid HGV	25	29	8.9
26T	Rigid HGV	27	30	7.5
32T	Rigid HGV	28	30	6.9
32T	Articulated HGV	33	33	5.2
38T	Articulated HGV	35	33	4.4
40T	Articulated HGV	-	34	-
44T	Articulated HGV	35	36	4.1

$^{\#}$ using RAC (2011) assuming driver salary of GBP 18,000, primarily light commercial vehicles

* calculated, assuming the vehicle is fully loaded and no empty running

Table 6. Parameter estimates for diesel consumption in LGVs

Variable	Description	Model L1 (autoreg.)	Model L2 (quad.trend)	Model L3 (no switch)
$\Delta lnDIS_{t-1}$	Lagged dependent variable (in log, differenced)	0.354 (2.99)***	-	-
$\Delta lnGDP$	GDP per capita (in log, differenced)	0.945 (2.93)***	0.833 (3.77)***	1.786 (5.29)***
$\Delta lnDPR$	Diesel price (in log, differenced)	0.037 (0.43)	0.018 (0.21)	0.211 (1.74)*
$\Delta TIME88$	Time trend from 1988 (differenced)	0.032 (3.05)***	0.147 (9.31)***	-
$\Delta TIME88SQ$	Quadratic time trend from 1988 (differenced)	-	-0.003(-6.78)***	-
$D89$	Dummy = 1 for 1989	0.245(10.95)***	0.224(15.39)***	0.352 (5.56)***
Diagnostics				
Adjusted R^2		0.818	0.885	0.591
AIC		-142.56	-166.18	-113.6
BIC		-133.88	-157.38	-108.3
Autocorr.	Breusch-Godfrey's LM test	0.243 (p=0.62)	0.754 (p=0.39)	9.9 (p=0.00)
ARCH effects	LM test	0.39 (p=0.53)	0.064 (p=0.80)	2.11 (p=0.15)
Normality	Shapiro Wilk test	1.132 (p=0.13)	0.773 (p=0.22)	-0.408 (p=0.66)
White noise	Portmanteau test	24.47 (p=0.18)	18.06 (p=0.52)	67.30 (p=0.00)

Statistically significant at *** 99%, ** 95%, * 90%