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Estimating the Rebound Effect of the U.S. Road Freight Transport

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Abstract

The United States (U.S.) road freight sector has continued to grow over recent decades. Growth in road freight could result in more fuel consumption and hence increased greenhouse gas emissions. Policymakers have attempted to manage the growth of energy usage through improved fuel economy based on technological advances. However, such improvements may not lead to anticipated goals because of the rebound effect, where improvements in energy efficiency trigger more travel and energy consumption that offsets energy savings. Thus, this study aims to determine the potential rebound effect from improved energy efficiency in the U.S. road freight sector. Eight fuel cost models are applied and asymmetric price response is incorporated in estimating the U.S. road freight sector's rebound effect from 1980 to 2016. In addition, a recently developed data envelopment analysis is applied to determine the annual rebound effect in the road freight sector. The results suggest that, after accounting for the asymmetric price response, the average rebound effect of the U.S. road freight sector ranges from 6.9% to 8.8%, a level considerably less than that found for several industrialized countries and emerging economies. However, a considerable increase in the rebound effect has been seen in more recent years. The findings suggest that overlooking the rebound effect in environmental policies could impede the goal of reducing total energy consumption and accompanying emissions. Policymakers should incorporate the rebound effect from efficiency enhancement in policy development and utilize some potential programs to reduce the adverse influence of rebound effect in related policies.

The United States (U.S.) freight sector has continued to expand over the past decades as a vital link in the nation's economic activities. In 2018, nearly 5.3 trillion ton-miles of goods were moved, with trucking as the dominant mode (*1*). Given the surging development of e-commerce, this growth is expected to continue. Freight growth is also because of the increasing imports of manufactured goods (*2*). Increased freight activities have resulted in more energy consumption that can also be affected by fuel efficiency, road condition, labor availability, and the load factor of heavy goods vehicles (HGVs) (*3*). The U.S. transport sector is the second-largest energy user among major economic sectors, accounting for more than 28% of all energy consumption in the U.S. (*4*). Among the transport sectors, road freight transport has the highest energy use and constitutes one-third of transport energy consumption in the U.S. (*5, 6*).

Energy consumption from rising freight transport leads to increases in greenhouse gas (GHG) emissions. The U.S. transport sector surpassed the electric power sector in 2016 to become the largest source of GHG emissions in the nation. Freight trucks produced 23% of U.S. all transport-based GHG emissions (*7, 8*). Therefore, reducing freight truck energy consumption through energy efficiency improvement is a primary focus of policymakers (*5*). To mitigate the rising trend of energy use and GHG emissions, the U.S. government has implemented national energy and environmental policies, such as the Energy Independence and Security Act in 2007 and the Clean Air Act in 2012, with the goals of improving fuel efficiency (gallons/1,000 ton-kilometer) and reducing GHG intensity (metric tons CO_2 eq./ton-kilometer) of HGVs (*9–11*).

However, the effects of the governmental efforts to lower GHG emissions are unclear, as anticipated reductions in total energy use may not be achieved. Presumably, improvement in technology and efficiency

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for energy service lowers its effective price, which will attract greater use. Accordingly, improvements in energy efficiency improvement may encourage more energy consumption thus offsetting energy savings from upgraded efficiency, which is referred to as the direct rebound effect (*12*). Further, financial savings because of the adoption of energy-saving technology can be expended on other goods and services that require freight services, which leads to the indirect rebound effect. Moreover, the rebound effect reflects asymmetric responses to energy price increases and decreases in both the short run and long run. An increase in energy price may decrease the rebound effect, whereas energy price reduction may amplify the effect (*13, 14*).

Several empirical studies have attempted to identify and estimate the rebound effect in the road transport sector. Small and Van Dender identified the rebound effect from the improved fuel efficiency in the U.S. passenger vehicle use (*15*). Llorca and Jamasb found the presence of the rebound effect in the European Union (EU) road freight transport sector after the EU adopted air quality, energy security, and climate change policies (*16*). Sorrel and Stapleton estimated the rebound effect in the United Kingdom's (UK) road freight sector based on static and dynamic models (*5*).

Given the rising concern in relation to GHG emissions and expected growth in freight, an updated study on the potential rebound effect associated with U.S. road freight transport is warranted. Further, previous studies on the energy efficiency of the U.S. road freight sector have generally overlooked the asymmetric nature of carriers' responses to price changes, which could lead to a biased estimate of the rebound effect (*17*). Therefore, the objective of this study is to identify the rebound effect for U.S. road freight transport given government policies that aimed at reducing energy consumption and GHGs emissions. Also, the related literature is complemented by considering the asymmetric energy price responses in the estimate of the rebound effects in U.S. road freight.

Literature Review

William Stanley Jevons first demonstrated that gains in energy efficiency improvement could lead to less energy savings, based on individual behavioral and systematic responses. Jevons, in his seminal paper titled "The Coal Question," argued that "it is ridiculous to reduce fuel consumption through using it economically and instead the opposite is true" (*18*). This concept is known as the Jevons Paradox. Clark and Foster illustrated Jevons' argument in relation to energy efficiency and consumption using an example of iron furnaces (*19*). If the furnace increases profitability by reducing the amount of coal used for the same level of output, new capital investment will be attracted and could result in increased iron production thereby lowering the final product (iron) price. Thus, the increased number of furnaces could offset the decreased average consumption of each furnace, which would eventually result in increased domestic coal consumption.

Khazzoom studied the components of the Jevons Paradox and showed that the demand for energy is price elastic in the long run; the rebound effect holds if a sufficient time span is considered (*20*). When actual energy savings are higher than the expected savings, the rebound effect is then negative. The price effect of an energy efficiency improvement is known as the direct rebound effect which includes both the substitution and income effects. The effect of spending the extra income from energy efficiency on the other goods or services is considered as the indirect rebound effect (*3*).

Ruzzenenti and Basosi concentrated on the energy efficiency of the freight sector in the EU as it is a pillar of the EU's strategy to meet the Kyoto protocol agreement (*21*). Using two different estimation approaches (econometric and network theory), they found a negative rebound effect in European freight transport, suggesting that actual energy savings are higher than the expected savings. However, some researchers found a positive rebound effect in the freight sector of the EU countries. Llorca and Jamasb examined the impact of the EU's newly adopted energy and environmental policies on energy consumption in the road freight transport sector of 15 European countries (*16*). They estimated the average direct rebound effect in the road freight sector to be 3.8%, with the highest effect found in Sweden at 7.9%. Also, the rebound effect in the road freight sector was higher in the more fuel-efficient countries compared with the less fuel-efficient countries. Matos and Silva found the direct rebound effect to be over 24% in Portugal's road freight transport sector, while Sorrell and Stapleton estimated the average direct rebound effect in the UK's road freight transport to be 49%, indicating that a 1% increase in energy efficiency will reduce energy consumption by only around 0.5% (*5, 22*).

Some researchers have paid attention to the rebound effect in emerging economies or developing countries. Wang and Lu estimated the direct rebound effect in China's road freight transport sector (*18*). They estimated that the direct rebound effects for the eastern, central, and western regions, and for all of China, as 52%, 80%, 78%, and 84%, respectively. A more recent study by Jin and Kim estimated the energy rebound effect of South Korea's aggregate economy and found a moderate rebound effect (*23*).

The definition of the rebound effect is related to the change in energy demand with a corresponding shock in the effective energy price. Frondel and Vance emphasized the importance of considering asymmetric price responses to improve the estimation of the rebound effect (*17*). Bentzen estimated the rebound effect in the U.S. manufacturing sector to be around 24% after incorporating asymmetric price responses (*24*). Stapleton et al. considered the asymmetric price responses in estimating the rebound effect in Great Britain's personal automobile transport and suggested an overall increase in the rebound effect for a fuel price decrease (*14*). Lin and Li incorporated asymmetric price responses in the model specification to estimate the rebound effect in China's heavy industry and found an increased rebound effect for energy price decreases (*13*).

Methods

Various definitions of the rebound effect have been introduced in previous studies. The use of negative price elasticity of energy service demand to estimate the rebound effect has been widely adopted as related data can be more easily obtained (*5, 25, 26*). As defined below, the rebound effect is:

$$RE = -n_{P_S}(S) = -\frac{\partial lnS}{\partial lnP_S} \tag{1}$$

where RE is rebound effect, P_s and S are energy cost and service demand, while $n_{P_S}(S)$ is the elasticity of service demand with respect to the energy cost of the service.

Following prior studies, road freight activity is measured in ton-kilometers (tkm), that is, tons of goods moved to the distances (*5, 21, 22*). Road freight levels could be influenced by various factors, such as production inputs, fuel cost, and gross domestic product (GDP) of the region. Fuel price, fuel cost, GDP, and energy efficiency of goods moved (ε) are the most widely used variables in estimating the rebound effect in the freight transport sector (*22, 23*).

The primary hypothesis in this study is that no rebound effect associated with energy efficiency improvement exists in the U.S. road freight transport sector. Fuel cost static and dynamic models are estimated to capture the short-run and long-run rebound effect following Sorrell and Stapleton (*5*). Static models define distance traveled of goods as a function of the same period explanatory variables. Since responses to efficiency improvements and fuel price changes take time, dynamic versions of each model are also estimated by taking the lag term of the dependent variable along with other explanatory variables.

The static fuel cost and the dynamic fuel cost are formed as Equations 2 and 3, respectively:

$$\ln Tkm_t = \beta_0^{SF} + \beta_1^{SF} \ln Y_t + \beta_2^{SF} \ln P_{St} + \mu_t \tag{2}$$

$$\ln Tkm_t = \beta_0^{DF} + \beta_1^{DF} \ln Y_t + \beta_2^{DF} \ln P_{St} + \beta_3^{DF} lnTkm_{t-1} + \mu_t \tag{3}$$

where Y_t is GDP, P_{st} is fuel cost, Tkm_{t-1} is a one-term lag of tkm, and μ_t is the error term of the model. In the static model, the elasticity of tkm with respect to fuel cost is given by the coefficient β_2^{SF}; whereas the elasticity is generated from (β_2^{DF} /(1 $-\beta_3^{DF}$)) in the dynamic model. Three additional variables, including a dummy variable of year 2012 (Year2012), an ultra-low sulfur diesel (ULSD) dummy, and manufacturing share of GDP, are considered to capture the potential effect of policy and industry development. A total of eight different models are estimated, including the base static model (static 1), three fuel cost static models (static 2–4), the base dynamic model (dynamic 1), and three fuel cost dynamic models (dynamic 2–4), with different combinations of the selected variables.

The selection of the models relies on the results of serial-correlation tests and heteroscedasticity tests for the error terms of each model. An endogeneity test is also performed for the GDP variable, as the residual of tkm and GDP might be related to some common factors, that is, fixed assets, the total number of employees, or unemployment rates (instrumental variables). Fit tests are also performed to find the compatibility of the instrumental variables in identifying the endogeneity issue of GDP. The test for under-identification, weak-identification, and over identification are conducted to examine if the instruments are valid for the analysis.

The per-gallon fuel prices are further decomposed to re-estimate the asymmetric price response to prevent the potential issue of biased estimation of the rebound effect. The decomposition technique proposed by Gately and Huntington is followed (*27*). The original fuel prices can be decomposed into maximum historical prices ($\max[\ln(P_{F,t})]$), cumulative sub-maximum price recoveries ($\text{rec}[\ln(P_{F,t})]$), and cumulative price decreases ($\text{dec}[\ln(P_{F,t})]$) as follows:

$$\ln(P_{F,t}) = \max[\ln(P_{F,t})] + \text{dec}[\ln(P_{F,t})] + \text{rec}[\ln(P_{F,t})] \tag{4}$$

where

$$\max[\ln(P_{F,t})] = \max[\ln(P_{F,1}), \ln(P_{F,2}), \ln(P_{F,3}), \ldots\ldots, \ln(P_{F,t})] \tag{5}$$

$$\text{dec}[\ln(P_{F,t})] = \sum_{i=1}^{t} \min(0, \{\max[\ln(P_{F,t-1})] - \ln(P_{F,t-1})\} - \{\max[\ln(P_{F,t})] - \ln(P_{F,t})\}) \tag{6}$$

$$\text{rec}[\ln(P_{F,t})] = \sum_{i=1}^{t} \max(0, \{\max[\ln(P_{F,t-1})] - \ln(P_{F,t-1})\} - \{\max[\ln(P_{F,t})] - \ln(P_{F,t})\}) \tag{7}$$

Each year fuel price ($/gallon) is decomposed to find price decreases and recoveries. After decomposition, recovery fuel price and decrease fuel price are used to generate P_e and P_s. These newly generated variables are used in the revised versions of the static and dynamic models (Equations 2 and 3) in estimating the rebound effects with changes in fuel prices.

Annual Rebound Effect from a Non-Parametric Analysis

Jin and Kim recently developed a novel method to estimate the rebound effect with time-series data (*23*). They argued that previous studies typically neglect the impact of energy intensity on the rebound effect. If the energy intensity of a sector is highly volatile over time, traditional rebound estimation may overestimate the actual rebound effect. Thus, they proposed an alternative definition as follows:

$$RE_t = \frac{E_{t,\text{actual}}}{E_{t,\text{potential}}} - 1 \tag{8}$$

where $E_{t,\text{actual}}$ refers to actual energy consumption and $E_{t,\text{potential}}$ refers to potential energy consumption that is derived from a data envelopment analysis (DEA). DEA is a non-parametric approach to measure the relative efficiency of the decision-making units (DMUs) based on a set of inputs and outputs (*23*).

Jin and Kim are followed, to adopt an aggregate rebound effect method to serve as a complementary to the structural equation model (*23*). First, the annual efficiency score is estimated using the slack-based DEA model (*28*). In this method, the sector's decision each year is considered as one DMU with tkm as the output and technological progress of the freight sector and energy consumption as the inputs. Technological progress is estimated from a Cobb-Douglas (C-D) production function comprising labor in the freight sector and new vehicle purchases as factors of production for tkm. The output-oriented slack-based DEA model is then used as follows:

Let,

$$X_{nt} = (X_{1t}, X_{2t}, \ldots\ldots\ldots\ldots, X_{nt})$$

$$Y_{lt} = (Y_{1t}, Y_{2t}, \ldots\ldots\ldots\ldots\ldots, Y_{lt}),$$

$$\text{Minimize } \rho = \frac{1 - \frac{1}{n}\sum_{n=1} \frac{S_n^x}{X_{n1}}}{1 + \frac{1}{l}\sum_{l=1} \frac{S_l^y}{Y_{l1}}} \tag{9}$$

Subject to,

$$\sum_{t=1} \lambda_t X_{nt} + S_n^x = X_{n1} \tag{10}$$

$$\sum_{t=1} \lambda_t Y_{lt} - S_l^y = Y_{l1} \tag{11}$$

$$\sum_{t=1} \lambda_t \geqslant 0 \tag{12}$$

$$S_n^x, S_l^y \geqslant 0$$

where X_{nt} is the vector of n inputs used by DMU t, while Y_{lt} is the vector of l outputs produced by DMU t. ρ is the energy efficiency score with $0 < \rho \leqslant 1$. S_n^x and S_l^y are the slack vectors of inputs excess, and outputs shortages, respectively. X_{n0} *and* Y_{l0} are the input and output values of the first DMU (t = 1). λ_t is the estimated weight vector that optimizes the linear combination of input and output vectors for DMU t. Robust DEA ("rDEA") package "R" software is used to estimate the efficiency score.

After obtaining the efficiency score, the annual rebound effect is then determined by measuring the overspent energy consumption following Equation 13 below (*23*):

$$E_{t,\text{potential}} = \text{efficiency}_t * \text{Tkm}_t * \text{EI}_t \tag{13}$$

where efficiency_t is the efficiency score generated from the DEA for DMU t. EI_t represents energy intensity which can be derived from dividing tkm by freight energy consumption. Plugging the estimated $E_{t,\text{potential}}$ in Equation 8 will then generate the yearly rebound effect.

Data

The dependent variable, tkm, obtained from the U.S. Bureau of Transportation Statistics (BTS) is estimated using two different methods before and after 2012. The estimate of tkm up to 2011 is based on the freight analysis framework 3 (FAF3) that considers the difference between the total of all modes and the sum of other modes without road (*29*). The 2012–2016 data are tabulated using the freight analysis framework 4 (FAF4) approach developed by the Federal Highway Administration (FHA) and the Oak Ridge National Lab (ORNL) (*30*). Fuel price (P_e) is measured as the price per megajoule (MJ) of energy consumption. GDP growth measures the economic output of a region (*31*). The energy efficiency (ε) of goods moved is defined as tkm divided by freight energy consumption. The fuel cost per tkm (P_{st}) is primarily influenced by how much it costs to travel 1 km and how much can be carried. Here, P_{st} is derived from dividing P_e by ε.

Following Sorrell and Stapleton, manufacturing's share of U.S. GDP is also included as an additional variable to account for the potential decoupling of freight from GDP (*5*). Similar to the UK, manufacturing's share of GDP in the U.S. has declined over time, while the imports of foreign manufacturing goods have replaced some freight demand from domestic manufacturing.

Table 1. Summary Statistics of Variables

Variables for static and dynamic models	Mean	SD	Min.	Max.
tkm (millions)	2,948,606	620,796	1,849,246	3,971,260
GDP per capita ($)	34,050.30	13,799.30	12,574.80	57,904.20
Fuel cost ($ per tkm)	0.03	0.01	0.02	0.07
Manufacturing share of GDP	0.43	0.10	0.29	0.67
Year2012 dummy	0.11	0.32	0	1
ULSD dummy	0.30	0.46	0	1
Instrumental variables to test endogeneity issue for GDP				
Fixed assets ($billions)	28,906.50	15,152.90	9,512.50	57,296.10
Employees (thousands)	1,436,253	203,717	107,6215	1,732,175
Unemployment rate	6.38	1.61	3.97	9.71
Factors of production for C-D production function				
Labor (thousands)	1,319.35	105.90	1,104.60	1,452.68
New vehicle purchases (thousands)	5,661.11	1,264.66	3,107	7,467

Note: SD = standard deviation; Min. = minimum; Max. = maximum; C-D = Cobb-Douglas, GDP = gross domestic product, tkm = ton-kilometer, ULSD = ultra-low sulfur diesel.

Thus, freight activity may become partially decoupled from GDP.

The Year2012 dummy variable is included to capture the potential influence of the Clean Air Act 2012, as more stringent regulations for cleaner highway vehicles are implemented under this act (*32*). Also, the dummy variable could capture the potential impacts of the switch of tkm estimation by the U.S. BTS. The dummy variable has a value of 1 after 2012, otherwise 0. An additional dummy variable is introduced to account for the imposition of ULSD use in freight transport starting in 2006 when the environmental protection agency (EPA) began to phase-in more strict regulations to lower the amount of sulfur in diesel fuel to 15 ppm (*33*). (ULSD reduces emissions and enhances fuel economy.) It is possible this policy has a rebound effect. The dummy variable has a value of 1 after 2006, otherwise 0.

Time-series data are collected from various sources for the period 1980–2016. Per capita GDP is collected from the World Bank (*34*). The value of manufacturing shipments is collected from the U.S. Census Bureau (*35*). Data on the instrumental variables, unemployment rate, and the total number of employees, are collected from the U.S. Bureau of Labor Statistics (*36, 37*). The value of fixed assets is collected from the Bureau of Economic Analysis (*38*). All other freight-related data, including tkm, energy consumption, fuel prices, freight labor, and the number of new vehicle purchases each year, are obtained from the U.S. BTS (*29*). The descriptive statistics of the data are summarized in Table 1.

Results and Discussion

Diagnostic tests indicate heteroscedasticity for both the static 1 and dynamic 1 models. Two static models (static 1 and static 4) exhibit endogeneity issues as independent variables are correlated with the residue terms. The serial correlation issue is found in the static models based on the Durbin-Watson (DW) *d*-statistic and two dynamic models (models 1 and 4) given the DW *h*-statistic. To correct for related serial correlation and heteroscedastic disturbance terms, a two-stage least squares (2SLS) estimation is applied with heteroskedastic and autocorrelation consistent (HAC) robust corrections (*39*).

The fit tests for the instrumental variables in each of the 2SLS models have also been conducted. The Anderson-Canon LM statistic shows that the under-identification issue is not detected in any of the estimated models as the null hypothesis of under-identification is rejected in all 2SLS models. Similarly, the weak-identification issue has also been rejected. The Cragg-Donald Wald *F* statistic indicates that the instrumental variables have strong explanatory power for the endogenous variables. The null hypothesis of the Hansen *J* statistic is not rejected, suggesting the instruments of all the models are valid and are not correlated with the error term in the system. Overall, the fit tests of the instruments indicate that fixed assets and the total number of employees are valid instruments for the endogenous GDP.

The 2SLS results of the static and dynamic fuel cost models are presented in Table 2. In the base static model, both GDP and fuel cost are statistically significant, suggesting both have an impact on freight tkm. A 1% increase in GDP increases tkm by 0.53%. In contrast, a 1% increase in fuel cost leads to a reduction in tkm by 0.14%. In static model 2, a 1% increase in the fuel cost now decreases tkm by 0.06% which is less than half the impact in the base model. The Year2012 dummy is statistically significant and captures the potential impacts of the tkm estimation method as well as the influence of the Clean Air Act. For model 3, all other variables are statistically significant. Similarly, fuel cost decreases to

Table 2. Parameter Estimates of the Static and Dynamic Models

Models	ln (GDP)	ln (fuel cost)	ln (lag tkm)#	ln (manufacturing share)	Year2012 dummy	ULSD dummy	Rebound effect
Static 1	0.52*** (0.037)	−0.14*** (0.04)	na	na	na	na	na
Static 2	0.58*** (0.019)	−0.06*** (0.023)	na	na	−0.23*** (0.020)	na	6.4%
Static 3	0.78*** (0.040)	−0.12*** (0.012)	na	0.37*** (0.071)	−0.22*** (0.009)	na	12.1%
Static 4	0.75*** (0.055)	−0.08** (0.028)	na	0.31*** (0.086)	−0.22*** (0.013)	−0.03 (0.028)	8%
Dynamic 1	0.12 (0.086)	−0.06 (0.037)	0.74*** (0.147)	na	na	na	na
Dynamic 2	0.43*** (0.096)	−0.05*** (0.015)	0.27* (0.157)	na	−0.18*** (0.039)	na	7.6%
Dynamic 3	0.62*** (0.127)	−0.08*** (0.016)	0.22 (0.149)	0.31*** (0.105)	−0.18*** (0.041)	na	na
Dynamic 4	0.65*** (0.078)	−0.05** (0.023)	0.18** (0.093)	0.28*** (0.086)	−0.19*** (0.024)	−0.04 (0.026)	6.3%

Note: GDP = gross domestic product, tkm = ton-kilometer, ULSD = ultra-low sulfur diesel; na = not applicable.
Percentage impact of the dummy variable (*D*) is estimated by 100 × [exp (*D*) – 1].
***, **, and * denote 1%, 5%, and 10% significance level, respectively. The numbers in brackets indicate the standard error.
#Only dynamic models include the lag term of tkm.

Table 3. Adjusted Rebound Effects Considering Asymmetric Price Response

	Original fuel price estimates	Average rebound effect	Recovery fuel price estimates	Average rebound effect	Decrease fuel price estimates	Average rebound effect
		8.8%		7.30% (17% decrease)		9.5% (8% increase)
Static 2	−0.064***		−0.070***		−0.048	
Static 3	−0.121***		−0.090***		−0.130***	
Static 4	−0.08**		−0.060***		−0.059***	
		6.90%		5% (27.5% decrease)		7.10% (2.9% increase)
Dynamic 2	−0.076***		−0.050***		−0.055**	
Dynamic 3	−0.102		−0.063***		−0.099***	
Dynamic 4	−0.063**		−0.038*		−0.060***	

Note: ***, **, and * denote 1%, 5%, and 10% significance level respectively.

–0.12%. In static model 4, the ULSD dummy is insignificant while the remaining variables are still significant. The rebound effects for the three static models range from 6.4% to 12.1%. An average of results from the three static models indicates that a 1% increase in fuel efficiency decreases fuel consumption by 0.9%.

The lag-dependent variable is significant in three of the four dynamic models. Also, GDP and fuel cost are significant in three of the four dynamic models. However, model results indicate that the impacts of both GDP and fuel cost on tkm are lower in the long run than in the short run. The Year2012 dummy has an average percentage negative impact on tkm across the four dynamic models of 16.8%. Manufacturing share is significant in dynamic models 3 and 4. As the long-run elasticity of goods moved in the dynamic framework is dependent on the significant estimates of fuel cost and lag term, the respective rebound effect is estimated to be 7.6% and 6.3% in dynamic models 2 and 4, respectively. The estimated rebound effects imply that a proportion of the potential energy and carbon savings from the improved efficiency in U.S. road freight has been partially offset by increased freight activity (more tkm). Results also show the dynamic models present relatively smaller rebound effects than the static models, suggesting that reliance on static models could lead to larger price elasticities (*40*).

The re-estimated results for the dynamic and static models from the price decomposition model are presented in Table 3. The table represents the rebound effects of recovery fuel price (P_{rec}) and decreased fuel price (P_{dec}) along with the original fuel price estimate for both static and dynamic models. All variables in the P_{rec} fuel cost are statistically significant. The rebound effects are averaged 7.3% and 5% for the static and dynamic models, respectively. These averages are lower than the original fuel price average rebound effect (8.8% in static, 6.9% in dynamic), suggesting the freight carriers use less energy with the price increase, and this results in a lower rebound effect. In the P_{dec} cases, the average rebound effects of the static and dynamic models are 9.5% and 7.1%, respectively, which are higher than the original rebound effect estimates, implying the increase of fuel consumption in responding to the reduction in fuel price.

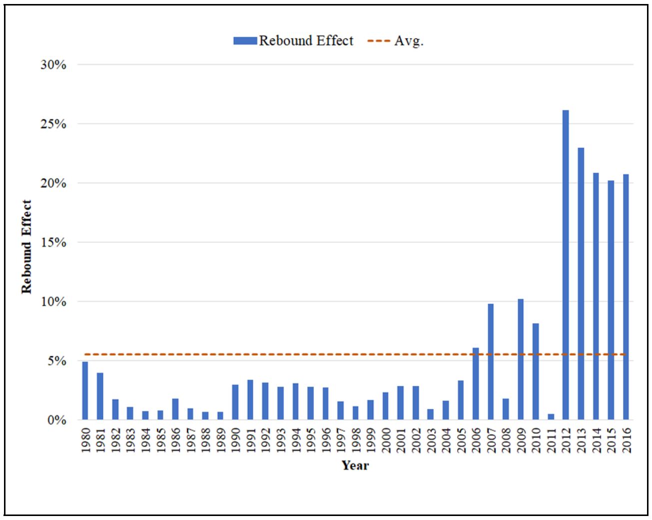

Figure 1. Annual rebound effect of the U.S. road freight transport from 1980 to 2016.

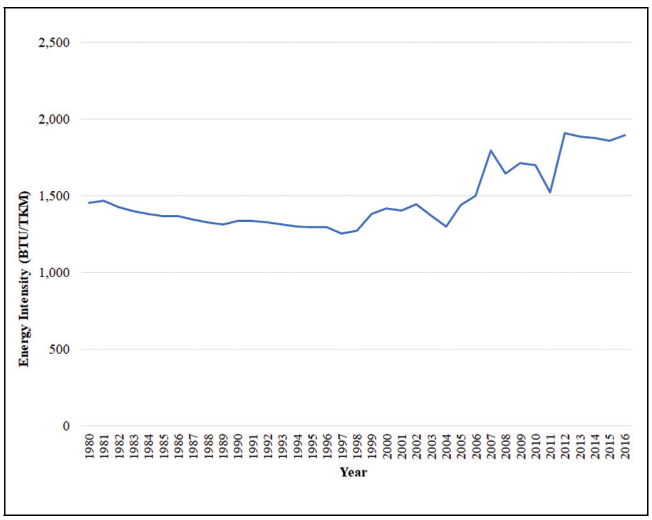

Figure 2. Energy intensity of U.S. road freight transport from 1980 to 2016 (*4, 30*).

Figure 1 illustrates the annual rebound effect estimated from the robust SBM DEA model. On average, the rebound effect of U.S. road freight transport is 5.5%, which is 20.3% less than the estimated dynamic fuel cost models. It is seen that the annual rebound effect was less than 5% in the period 1980–2005. From 2006 through 2010, it typically ranged between 5% and 10%. However, from 2012 to 2016, it dramatically increased to the 21%–26% range. The surge in road freight's rebound effect in the later period could be potentially related to the Clean Air Act 2012 that requires higher fuel efficiency vehicles for freight. The improved fuel efficiency may reduce the fuel cost. As travel cost decreases in the U.S. road freight sector, there might be less incentive to have full loads, which eventually increases energy intensity along with tkm (*41*). It explains the volatility with a boost in the energy intensity of the U.S. road freight sector shown in Figure 2.

Comparing with other countries, the rebound effect of U.S. road freight is higher than those estimated for European countries with an average of 3.8% reported by Llorca and Jamasb, while markedly lower than estimates for both Portugal and the UK (*16*). Among those examined countries, China has the highest rebound effect (84%) for the road freight sector (*18*).

Several factors may contribute to the variability in the rebound effect over time in this study. First, the types of commodities to be transported by freight transport can be an important factor for the high variability of freight rebound effect across time. According to Li et al., bulk commodities like logs, lumber, and textiles are shown to be less elastic than non-bulk commodities like paper, plastic, and rubber products (*42*). Hence, the estimation results reflect the situation that the tkm generated by the trucking is mostly associated with bulk commodities. Bulk commodities, for example, meat, seafood, coal, and motorized vehicle machinery, among others, moved by road freight transport in the U.S. have increased over time (*30*). Hence, the rebound effect is slightly higher in the short run but lower in the long run. The shift in the composition of freight movement could be because of changes in shipping distance, including origin and destinations, and to changes in the sectoral composition and location of economic activity (for example, primary producers of certain products—seafood, red meat, dairy, and horticulture, among others, have perhaps become increasingly geographically concentrated) (*43*).

Second, Christdis and Leduc stated that shorter shipping distances tend to be less elastic than long shipping distances (*44*). According to the U.S. Department of Transportation, and Winebrake et al., the majority of the HGV shipping in the U.S. is for shorter distances, that is, less than 500 mi, which may explain smaller rebound effects in U.S. road freight transport (*41, 45*). Also, distance is closely related to the availability of competing modes for commodity shipping.

Third, the availability of alternative modes might have an impact on freight elasticity. This availability is also dependent on factors like regional infrastructure and shipping distances. Christdis and Leduc showed, generally, the shorter the shipping distance, the greater the possibility of only one modal option availability (*44*). Rich et al. showed that, when the shipping distance is longer, rail and barge are often available alternatives, which increases the ability to respond to price changes (i.e., elasticities increase) (*46*). Specifically, rail availability as an alternative to truck allows the companies to consider the cross-price elasticities between modes. Winebrake et al. indicated that smaller elasticities hint at a potential shift from rail to truck in the U.S. because of changes in HGV freight prices given increased fuel efficiency (*41*). Lower freight elasticity found in this study indicates there might be a shift of shipping from rail to truck to accommodate the relative growth in shorter shipping distance. However, the large-scale shipments weighing between 25 and 40 tons and greater than 500 mi are more suited to rail (*9*).

Conclusion

One of the main objectives of energy and emissions policies is to reduce energy consumption for major consuming sectors like the road freight sector. Energy consumption reduction can be done through fuel economy improvement. However, such improvements lower the marginal cost of supplying energy service that may in turn increase energy consumption thus eventually offsetting the expected energy efficiency gains (i.e., creating a positive rebound effect). This study estimates the rebound effect in the U.S. road freight sector for the period 1980–2016. Based on eight fuel cost models, including four static and four dynamic models, the results suggest that the short-run rebound effect ranges between 6.4% to 12.1%, and the long-run rebound effect is around 7% in the U.S. road freight sector. Further analyses show that the average rebound effects are lowered to 7.3% for the static model (i.e., the short-run estimates) and 5% for the dynamic model (the long-run estimates) after adjusting the price response asymmetries in the estimation. In addition, over the study period, the rebound effect was initially less than 5%, increased to around 10% in 2007, but dramatically increases to an average of 22.2% after 2011.

Despite the increasing rebound effect in the U.S. road freight sector over the study period, it is still less than the rebound effect found in other developed countries and emerging economies. The variability of the U.S. rebound effect over time could be linked to several factors such as commodity types, shipping distance, modal share, and geographical location. In addition, the estimation method of tkm by the U.S. Bureau of Transportation Statistics and ORNL could contribute to this volatility, as freight analysis framework (FAF) tkm is based on traffic assignment rather than the actual odometer readings. Moreover, annual updates of FAF data are driven mostly by assumptions and not collected from the field except for survey years.

These results have important policy implications. The estimated rebound effect proves to be a deterrent to the energy efficiency policies when the actual energy consumption exceeds the anticipated reduction from the policies. Overlooking the rebound effect in the development of energy or environmental policies could result in more energy consumption and related GHG emissions even when the goal of the policy is to mitigate environmental degradation. However, the rebound effect should not be used as a rationale for inaction in addressing the energy and environmental issues. Instead, policymakers should take the rebound effect generated from efficiency enhancement into account in the policy development to better gauge the impact of related policies.

Some specific policies have been suggested as the potential remedies to reduce the adverse influence of the rebound effect in energy and environmental policies. For instance, a systematic cap-and-trade scheme has been suggested as an effective approach to address the rebound effect associated with energy efficiency improvement (*16, 47*). Also, sector-specific energy or environmental tax, for example, carbon tax, could serve as an alternative strategy in mitigating the rebound effect, assuming the pricing for carbon is adequately estimated (*3, 47*). In addition, altering consumption patterns by using consumption information and standardization could enhance the effect of carbon tax (*47*). Combining those policies could lower burden-shifting among economic sectors and further reduce the negative consequences of the rebound effect.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: T.E. Yu; data collection: A.L. Patwary; analysis and interpretation of results: A.L. Patwary; draft manuscript preparation: A.L. Patwary, T.E. Yu, B.C. English, D. Hughes, S. Cho. All authors reviewed the results and approved the final version of the manuscript.

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Data Accessibility Statement

The data used for analysis in this study are generated from a variety of public domain resources, that is, the U.S. Bureau of

Transportation Statistics, the World Bank, the U.S. Census Bureau, the Bureau of Labor Statistics, and the Bureau of Economic Analysis (*29, 34–38*).

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