Estimating rebound effect for passenger cars and its effects on US policy regulations

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SHORT SUMMARY

Policies regulating the fuel economy of passenger vehicles have been implemented by many nations around the world to mitigate greenhouse gas emissions and improve energy efficiency. Such policies lead to advancements in-vehicle technology and improved fuel efficiency which then reduce per-mile driving costs. This reduction in passenger vehicle driving cost may result in the rise of vehicle miles traveled, which is referred to as the rebound effect. This study aims at estimating the rebound effect and at covering the difference (if any) between the rebound effect and gasoline price elasticity to vehicle miles traveled. The analysis is based on the 2017 National Household Travel Survey. We estimate a rebound effect in the range of 20%-26%, with estimation consistent across Ordinary Least Square (OLS) and Instrumental Variable (IV) approach. Interestingly we observe an absence of rebound effect in vehicles up to three-year-old and a much smaller rebound effect in hybrid vehicles.

Keywords: Rebound effect, SAFE rule, transport policy, vehicle technology, vehicle miles traveled.

1. INTRODUCTION

A policy making process often involves understanding the intuitive and counter-intuitive effects deriving from that policy and its instrumentation. Reducing the energy use and greenhouse gas (GHG) emissions being a crucial part of maintaining environment standards, the U.S. strategy has been majorly centered on the Corporate Average Fuel Economy (CAFE) and the GHG emission standards for passenger vehicles. The 2018 Notice of Proposed Rule-Making (NPRM) by the National Highway Traffic Safety Administration (NHTSA) and US Environmental Protection Agency (EPA) proposes the Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule for Model Years 2021-2026 passenger cars and light trucks. The EPA and NHTSA proposed rule change would defer implementing more stringent CAFE mileage standards. This is expected to reduce light vehicle fuel efficiency and increase fuel consumption and the associated GHG emissions. On the other hand, reduced vehicle prices will make new vehicles more affordable and increase total number of vehicles on the road. EPA/NHTSA seeks to monetize these effects and present their results evaluated in present value terms for comparison. An important component and indeed parameter of these analyses is the evaluation of consumers' response to the projected changes in vehicular price and efficiency for model years 2021-2026.

Advancements in technology improve both the fuel economy and vehicle performance. An improvement in fleet-wide fuel economy reduces the CO_2 emissions. However, the incremental benefits of improving fuel economy decrease, indicating that a fewer gallons of fuel will be saved from subsequent incremental improvements. On the other hand, enforcement of stringent standards on fuel economy and CO_2 emissions increase the vehicle prices, averting the consumers from using newer and cleaner vehicles. An efficient policy by the government should be instrumented in the lines of establishing standards that promote both energy conservation and safety in the light of what is viable, both technologically and economically. Numerous studies have analyzed the various aspects of fuel efficiency (West & Pickrell, 2011; Gillingham, 2011; Greene, 2012; Linn, 2016), including basic engine design parameters and vehicle motor transmission, from the perspective of meeting the ever-increasing stringency of US Federal CAFE standards. Other studies have investigated the effect of tax reforms on GHG emissions from private transportation (Wadud, Graham, & Noland, 2009), effects of fuel economy and using gasoline tax on gasoline consumption (West & Pickrell, 2011). Primary conclusions from these studies indicate that the gasoline tax is less compared to the vehicle user's per gallon of gasoline saved. Evidently, the advancements in vehicle technology reduce the per-mile driving cost of passenger vehicles. A trivial implication of the same is reduction in gasoline usage and thereby reduction in GHG emissions. However, a rebound effect may also be triggered with better fuel efficiency; that is, the users tend towards increased vehicle usage and/or resort to bigger vehicles. This compromises the gains of fuel efficiency. An increased magnitude of such rebound effect may even result in outcomes contradictory to the expected, which in this case could be a failure to achieve desired emission targets. Instrumenting the policies with reducing gasoline consumption and GHG emissions as primary goals should give an adequate consideration for such effects.

In summary, the majority of studies in the literature indicate a rebound effect lower than 20% (Hymel, Small, & Dender, 2010; Hymel & Small, 2015; Gillingham, 2011; Su, 2012; Langer, Maheshri, & Winston, 2017; Knittel & Sandler, 2018; Wenzel, 2018). However, some references do show very high values of rebound effect, especially (West & Pickrell, 2011) who found a rebound effect of 27% for three vehicles households, and (Linn, 2016) who estimates values in the range of 20% - 40%. All the evidences provided suggest that the possible range of the magnitude of the rebound effect is wide and that heterogeneity might exist across households types and possibly different fuel type vehicles, especially with the introduction of hybrid and more efficient vehicles in the marketplace.

The objective of this study is to model the effect of fuel economy standards and to undercover the difference between price elasticity to demand of gasoline and the rebound effect for household vehicle usage decisions. Ultimately, the results expected should help better understand the consequences of the EPA's new proposed standards for fuel economy and its impact on consumer behavior.

Rebound Effect

Every advancement in technology is accompanied by a gain in terms of the use of resources. For example, a new technology in vehicles allows for a better fuel efficiency, indicating the amount of fuel consumed per mile of travel reduces. However, there is a mismatch between the actual benefit obtained by the technology to the estimated benefit, attributing to other systemic responses and behavioral factors. Typically, the actual benefit obtained is less than the estimated ones. In the case of fuel efficient cars, the consumers tend to use the cars more than the regular use because of the reduced driving costs and thereby increasing the fuel consumption compared to the estimated values. This behavior implies that a portion of the energy savings and reduced emissions that would have been obtained with unchanged behavior are compromised, diminishing the effectiveness of such improvements. This consumer response to improved fuel efficiency of vehicles is known as rebound effect. Quantitatively, the rebound effect is the elasticity of the demand for driving with respect to a change in fuel efficiency.

2. METHODOLOGY

The objective of the modeling exercise is twofold. Firstly, to estimate the fuel economy rebound effect i.e. elasticity of the vehicle miles traveled (VMT) to the fuel economy (MPG). Secondly, to estimate the elasticity to fuel price and undercover the difference across these two elasticities. We adopt two different estimation techniques: Ordinary Least Squares (OLS) regression and the Instrumental Variable (IV) approach. In all our model the dependent variable is the log of VMT for each vehicle in the household; several independent variables have been considered, those include the log of fuel price, log of MPG, the average MPG value of other vehicles in the same household, household income, number of vehicle holdings, household size, number of adults, workers, and drivers, type of residence location, urban area size, metropolitan region size, and age, educational status of the vehicle primary driver.

Data description

The primary data source for this study is the 2017 National Household Travel Survey (NHTS), which is a US nationally representative survey of travel behavior conducted from April 2016 through April 2017. The sample consists of 129,696 households and 256,115 vehicles. The data contains household's demographic information such as household size, composition, income, geographic information such as the state of residence, local residential density, metropolitan statistical area, and information on each household's automobile holdings (by make, model, and year) and annual vehicle miles travelled. In this study, we restrict our attention to households with passenger cars and so exclude household vehicles that are pickup trucks, RVs, motorcycles, and other non-standard vehicles due to the seasonal nature of their use. Further excluding observations with missing information of required variables (like annual mileage, vehicle age or certain household characteristics), our sample consists of 188,009 vehicle observations.

Our quantitative analysis and all the models presented in this paper are based on the variable "BESTMILE" as calculated in the 2017 NHTS. There are several reasons that motivated our choice. First, "BESTMILE" is explicitly mentioned in the NPRM; second, most of the models available and elasticity values in the literature are based on this measure; third, NHTS data is publicly available and it is a nationally representative sample of the US population.

Model Specification

In general, the demand for driving or VMT on a vehicle i of household h can be expressed as a function of the fuel price P_h, characteristics of the household, land use and primary driver Z_h, vehicle specific characteristics η_i, fuel economy of the vehicle being driven $MPG_{h,i}$ and fuel economy of the other vehicles $MPG_{h,-i}$ if the household owns multiple vehicles.

$$VMT_{h,i} = f\left(P_h, MPG_{h,i}, MPG_{h,-i}, Z_h, \eta_i\right)$$

Considering a log-linear relationship between the VMT and the other variables, the VMT of the i^{th} vehicle of the household h is given by

$$\ln VMT_{hi} = \beta_0 + \beta_1 \ln P_h + \beta_2 \ln MPG_{hi} + \beta_3 \ln \overline{MPG}_{h,-i} + \gamma_Z Z_h + \gamma_\eta \eta_i + \varepsilon_{hi} \tag{1}$$

Here, the new variable $\ln \overline{MPG}_{h,-i}$ represents the log of mean of fuel efficiency of the household's other vehicles. This equals zero for households owning only one vehicle. The variables Z_h and η_i represent the set of controls for household and vehicle characteristics respectively. $\varepsilon_{h,i}$ is a mean-zero error term that models all the variations in the VMT that can not be realized using the previous variables. β_0, β_1, β_2 and γ are parameters to be estimated. The slopes β_1 and β_2 model the elasticity of the VMT to the variations in gasoline price and fuel economy respectively.

Adopting OLS approach to identify the causal effect of vehicle fuel efficiency on the driving is based on assumption of absence of simultaneity between household's choice of MPG and extent of driving. Vehicle's fuel economy and intended vehicle use are interrelated, for example, households with long distance commuters may buy vehicles that have high fuel efficiency to save on the driving cost, resulting in correlation between MPG and the error term in the vehicle usage equation. So, potential bias from simultaneity between MPG and vehicle usage is addressed by employing instrumental variable (IV) approach in a two-stage least squares framework. Moreover, the use of OLS to calculate rebound effect might yield biased estimates due to the following situations. Firstly, since the fuel economy data come from a secondary dataset, the OLS does not control the measurement error. Secondly, since the vehicle's fuel economy data is obtained just by matching the vehicle vintage, make and model, the exact correlation between the obtained vehicle' fuel economy and other characteristics of such vehicle is not captured. Third, the vehicle's fuel economy is also correlated with household characteristics included in equation (1). Consequently, instrumenting the vehicle's fuel economy using vehicle characteristics and their interaction with household level information is expected to result in relatively stable estimates. We instrument the fuel economy of a vehicle using vehicle age interacted with household vehicle count and vehicle type specific dummies. This interaction between household and vehicle characteristics allows for greater household heterogeneity in unobserved preferences for driving. (Linn, 2016) uses a similar instrumental variables (IV) approach to estimate vehicle's fuel economy. Differently, the instruments used by (Linn, 2016) include the interaction of household characteristics effects with the gasoline price at the time of purchase. This was made possible because the 2009 NHTS included the month of vehicle purchase which was linked to the respective monthly fuel price.

To address the omitted variable bias and reverse causality, we instrument MPG with vehicle age interacted with the number of household vehicles, and vehicle types. We validate the choice of instruments (Z_{hi}) based on the following two assumptions (i) they are correlated with fuel economy i.e., $cov(Z_{hi}, MPG_{hi}) \neq 0$, while (ii) the instruments have no direct causal effect on the outcome variable following the exclusion restriction of the econometric theory, meaning that the instruments only affect the dependent variable by affecting MPG.

3. RESULTS AND DISCUSSION

Table 1 presents the results obtained with the IV approach; for each column (labelled 1 to 4) the same set of predictors is considered. Table 2 presents the IV estimates obtained for different vehicle categories; this analysis is aimed at understanding heterogeneity in the use of old and new vehicles, across fuel types, and in household with different number of cars (if any).

Table 1: Effects of Fuel Prices and Fuel Economy on VMT using Instrumental Variable approach

	(1) **No restriction on BESTMILE**	(2) **BESTMILE estimated using approach-1**	(3) **Controlling for new car**	(4) **Fuel cost and MPG are considered as endogenous**
log(Fuel cost)	-0.250***	-0.255***	-0.246***	-0.254***
	(0.019)	(0.020)	(0.019)	(0.020)
log(Fuel economy)	0.324***	0.260***	0.285***	0.321***
	(0.0140)	(0.016)	(0.014)	(0.014)
log(Avg of other vehicle's MPG)	-0.057***	-0.058***	-0.055***	-0.057***
	(0.002)	(0.002)	(0.002)	(0.002)
New car dummy	-	-	0.183***	-
	-	-	(0.005)	-
No. of observations	180,626	156,038	180,626	180,626
R^2	0.084	0.088	0.090	0.084
F-statistic	12967	11135.04	12967	6062.77; 13800
Rebound Effect	**0.267**	**0.202**	**0.230**	**0.264**
Instruments for fuel economy	Vehicle age interacted with number of vehicles, type of the vehicle			

Notes: Each column reports a separate regression. Standard errors are reported in parentheses. '***', '**', and '*' denote statistical significance at the 1%, 5%, and 10% level, respectively. The dependent variable is the log of VMT. The table reports coefficients of log fuel price, log fuel economy, and log of the average fuel economy of other vehicles. For regressions from column 1 to 3, only fuel economy is instrumented. For column 2, bestmile is considered only when constructed with complete information of the odometer reading, self-reported VMT, and info on primary driver (approach-1). Column 3 presents the estimates when we include a dummy indicating whether the car is bought in the last three years of the survey. Column 4 presents results when both fuel economy and fuel cost are considered as endogenous and the latter being instrumented with household state dummies, and group dummies by combination of census division, MSA status, and presence of a subway system. Observations that exceed the top and bottom 1% of BESTMILE are excluded. The F-statistic for the test that all coefficients of instruments for in first stage are equal to zero indicate that these predictors are statistically significant. Two F-statistic values reported at the bottom of Table 1 column 4 are for instruments to model the fuel price and fuel economy respectively.

Table 2: Effects of Fuel Prices and Fuel Economy on VMT of Various Categories of Vehicles

(a) Vehicle Age

	New Car	**Old Car**
log(Fuel cost)	-0.168***	-0.248***
	(0.038)	(0.022)
log(Fuel economy)	-0.327***	0.223***
	(0.036)	(0.016)
log(Avg of other vehicle's MPG)	-0.028***	-0.060***
	(0.005)	(0.002)
No. of observations	26,581	154,045
R^2	0.091	0.082
Fuel Economy Rebound Effect	-	0.163

(b) Fuel Type

	Gasoline	**Diesel**	**Hybrid**
log(Fuel cost)	-0.278***	0.084	-0.355***
	(0.021)	(0.280)	(0.043)
log(Fuel economy)	0.362***	0.163*	0.151***
	(0.018)	(0.090)	(0.054)
log(Avg of other vehicle's MPG)	-0.058***	-0.086***	-0.046***
	(0.002)	(0.025)	(0.011)
No. of observations	173,182	1,540	5,783
R^2	0.084	0.106	0.086
Fuel Economy Rebound Effect	**0.304**	**0.077**	**0.105**

(c) Households with different ownership

	1 veh HH	**2 veh HH**	**3 veh HH**	**4+ veh HH**
log(Fuel cost)	-0.109**	-0.235***	-0.273***	-0.314***
	(0.046)	(0.020)	(0.040)	(0.048)
log(Fuel economy)	0.139***	0.362***	0.515***	0.528***
	(0.032)	(0.018)	(0.025)	(0.031)
log(Avg of other vehicle's MPG)	-	-0.042***	0.042***	0.090***
	-	(0.010)	(0.016)	(0.020)
No. of observations	35,048	75,287	39,746	30,545
R^2	0.124	0.099	0.091	0.086
Fuel Economy Rebound Effect	**0.139**	**0.32**	**0.557**	**0.618**

Each column reports a separate regression using IV approach. Standard errors are reported in parentheses. '***', '**', and '*' denote statistical significance at the 1%, 5%, and 10% level, respectively. The dependent variable is the log of VMT. Panel A presents the different estimates between new and old vehicles. The new cars are those vintage is less than or equal to three years. Panel B reports the estimates for vehicles when classified based on their fuel type. The hybrid category includes plug-in hybrid, battery electric and conventional hybrid cars. Panel C reports the estimates for vehicles when classified based on the household vehicle ownership count. Observations that exceed the top and bottom 1% of BESTMILE are excluded.

Overall, our results provide evidence of rebound effect suggesting that improvement in fuel economy may induce more travel and thereby offset the actual GHG benefits. We adopt two statistical methods to regress VMT on fuel price, miles per gallon, and cost per mile: the Ordinary Least Square (OLS) regression and an Instrumental Variable (IV) Approach. Based on the analysis, we estimated a rebound effect in the range of 20% to 26%, where instrumented model suggested relatively higher rebound estimate. The results of this study indicate that by using instruments to control for simultaneity and omitted variables, a higher vehicle use sensitivity to improvements in the fuel efficiency is observed. Further accounting for endogeneity in fuel cost, yields no significant difference in the point estimates (from column 1 and 4 in Table 1). The rebound effect found in this study is towards the lower end of the range observed by (Linn, 2016) and thereby strengthening the fact that rebound effect is declining over time as suggested by (Dimitropoulos, Oueslati, & Sintek, 2018).

Across models with IV specification, we find unequal effects of fuel price and fuel economy on the vehicle travel i.e., elasticity of vehicle travel with respect to fuel economy is greater than the fuel price elasticity. In contrast, (Greene, 2012; Stapleton, Sorrell, & Schwanen, 2016) find little or no evidence of statistical significant effect of fuel economy on fuel use. An average fuel price elasticity of about -0.25 is identified that corresponds to the findings of (Bento, Goulder, Jacobsen, & von Haefen, 2009; Hymel & Small, 2015), but are higher than the estimates found in (Gillingham, Jenn, & Azevedo, 2015; Linn, 2016; Wenzel, 2018; Knittel & Sandler, 2018).

In addition, when accounting for the age of the vehicle and in particular when regressing VMT of newer vehicle less than three year old, we found an absence of rebound effect and a lower elasticity to gas price. The older vehicles are found to be much more responsive to changes in fuel price (Gillingham, 2011) and for them we estimate a rebound effect of 0.16. The estimates for vehicles of different fuel type reveal that people driving hybrid-electric vehicles have a lower elasticity to fuel economy (0.15) and thus lower rebound effect (0.10). The results from our study provide evidence of a higher responsiveness to fuel cost when compared to fuel efficiency for gasoline vehicles, whereas an opposite effect is observed in the case of hybrid vehicles suggesting a shift in consumer preferences with the newer and relatively fuel efficient vehicles. In general, the effect of the efficiency of other vehicles in the household is small but statistically significant over different specifications. Further, the study also captures the changes in travel demand across households of different vehicle ownership in response to changing fuel prices. The results indicate that as the number of cars owned by the household increases, their sensitivity to changes in fuel price also increases (West & Pickrell, 2011). In addition, we obtain rebound effects of 14%, 32%, 56%, and 62% for households with 1, 2, 3, and 4+ cars using IV approach. The fact that households with multiple cars have the opportunity to shift among vehicles may result in a larger rebound effect when compared to household with single car (Weber & Farsi, 2014). Moreover, vehicle ownership reflects the income associated with the household (Liu, Tremblay, & Cirillo, 2014) and thus suggesting that it is likely to observe an increase in the rebound effect with vehicle ownership.

To conclude, the findings of this study play an important contribution to the bulk of studies that uses regional data or aggregated data, since we use nationally representative disaggregate data and make an attempt the classify the rebound estimates across different vehicle categories. Although the rebound effect estimated in this study slightly aligns with the central estimate adopted by the NPRM, a more stringent analysis over a larger time period is suggested considering the recent changes in the vehicle fleet with the introduction of hybrid and electric vehicles. Since NHTS is a cross-sectional data, the rebound effect estimated in this study is considered a long-run estimate. Further, the rebound estimates from this study fall in range with many other long run estimates based on data from US, regardless of the differences in econometric technique adopted.

4. CONCLUSIONS AND POLICY IMPLICATIONS

For decades the US Federal Government has sought to establish Corporate Average Fuel Economy (CAFE) mileage efficiency standards in order to promote gasoline conservation objectives for US auto manufacturers. Then later through the Clean Air Act the US EPA has tried to regulate GHG auto emissions in coordination with the CAFE MPG requirements. Thus it is important to understand the determinants of US consumer driving behavior in order to assess the effectiveness of new CAFE requirements. Economic theory predicts that consumers will seek to optimize prices by adjusting their choice behavior in reaction to changes in the price and efficiency parameters affecting their choices. In this study, the focus has been on the prediction of the effects of the US Government's revision to CAFE MPG for the future vehicle model years 2022-2025.

The data based evidences in this paper are indicative of new trends in travel behavior. The choice to buy a more efficient or new technology vehicle is not motivated only by the need or desire to drive more, but might be the results of others considerations. For one, this study attests that high values of rebound effect are found for households with a high number of vehicles. Nowadays, millennials appear to have a preference against traditional living in detached single-family houses with multiple personal vehicles to meet family transportation needs. Rather their preference favors denser multifamily living in high-rise type buildings with more compact O-D for home-work, local shopping, and more use of walking or biking or public transportation. Second, in order to reduce GHG emissions, there has been considerable emphasis on the substitution of alternative fueled cars, in particular, electric-powered vehicles in place of gasoline-powered vehicles. In the future, more investments will be placed on electric and hybrid-electric vehicles or other more advanced fuel-efficient choices such as hydrogen or fuel cells, and so forth. Our results clearly demonstrate the absence of rebound effect in newer vehicles, and less sensitivity to MPG for hybrid-electric vehicles. Third, where alternatives permit, preference for auto ownership seems to be in a state of decline and more reliance on alternative transportation modes with substitution of shared riding services for private vehicle ownership. Although shared mobility is not directly accounted for in this study, we have shown that the MPG of other vehicles in the household affect the value of the rebound effect; in the future we could expect that more miles will be placed on more efficient alternatives, including not privately owned vehicles. Fourth, socio-economic changes due to US and worldwide population aging. This is bringing about changes in wealth and income distribution as these factors influence consumer means and mode choices. Income and spatial characteristics are part of our model specification and can be update when new data will be available. Fifth the effects of the worldwide pandemic on workplace choices and decisions by both employers and their employees are not yet well known and are expected to be an important factor for future analysis. Lastly, there is a rather obvious worldwide recognition of increasing the importance of GHG, including CO_2 and other gases as these factors influence consumer attitudes incorporated into their buying preferences. As a result of the above uncertainties and gaps in current knowledge factors, there will be a continuing need to reassess the rebound effect considered in this study.

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