Estimating Medium-run Direct Rebound Effects of the footprint-based CAFE standard

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Estimating Medium-run Rebound Effects of the CAFE Standard

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Abstract

A new footprint-based mechanism was introduced to the Corporate Average Fuel Economy (CAFE) standard in 2012, and we observe a substantial change in the relationship between fuel economy and other primary vehicle attributes. To the extent that the new mechanism affects the optimal set of vehicle attributes, it would also affect the driving behavior of households owning vehicles that are newly remodeled after 2012. In this paper, we estimate the fuel-economy rebound effect in a way that distinguishes the per-mile cost reduction (fuel-cost effect) and bundle quality adjustment (quality-adjustment effect), both of which occur when fuel economy is improved. Using the 2017 National Household Travel Survey (NHTS) of approximately 110,000 vehicles representative of U.S. population, we estimate the rebound effects by taking a two-step approach and utilizing vehicle remodeling cycles as a new source of variation. The results show that the fuel-cost rebound effect was 8.9% between 2005 and 2016. We then find that the quality-adjustment effect was as much as 9.2% during the period. This quality-adjustment effect completely offsets the fuel-cost rebound effect and yields a 0% fuel-economy rebound effect. The quality-adjustment effect reduced to 2.0% after 2012, suggesting that the fuel economy improvement was achieved with milder quality adjustment than before. Failing to account for the quality-adjustment effect resulted in an overestimation of the true fuel economy rebound effect by 11.0%-points between 2005 and 2011 and by 3.1%-points after 2012.

Keywords: Rebound Effects, Fuel Economy, CAFE Standard
JEL Codes: D22, H25, Q58

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1 Introduction

Aiming to curb greenhouse gas and other pollutant emissions, the U.S. government has introduced energy-efficiency standards to a variety of household appliances and automobiles over the past decades. Energy economists, however, have found that such standards entail a type of behavioral failure called "rebound effects," suggesting that ex-ante engineering estimates of energy savings will unlikely be achieved due to increased energy consumption by consumers encouraged by the saved energy costs.[1] Precisely estimating the magnitude of rebound effects is essential to attaining the intended energy savings and evaluating the efficiency and welfare effects of such standards. In the U.S. automobile sector, the Corporate Average Fuel Economy (CAFE) standard has been recognized as one of the most influential energy-efficiency standards, which has almost doubled the industry-wide average fuel economy since its enactment in 1975 through 2018 (US EPA, 2019). The U.S. Environmental Protection Agency (EPA) had employed a 10% rebound effect in their cost-benefit analysis of the CAFE standard. In 2018, however, the EPA of Trump Administration proposed a rollback of the CAFE standard (U.S. EPA and DOT, 2018), where they doubled the magnitude of the rebound effect to inflate the benefits from avoided accident-related fatalities. A group of economists swiftly criticized that the agency justified the change based on selected rebound estimates in favor of their scenario, and that they ignored more recent and reliable estimates which suggested smaller rebound effects. (Bento et al., 2018).

In the economics literature, rebound effects of the CAFE standard are typically estimated as the elasticity of Vehicle Miles Traveled (VMT) with respect to either fuel economy or per-mile driving costs. To obtain more reliable rebound estimates, recent studies have increasingly utilized micro data such as odometer readings of individual vehicles in some

[1] In this paper, we use the term "rebound effects" to indicate direct rebound effects unless otherwise noted. The direct rebound effect refers to the percentage of forgone energy savings from the regulated good due to an increase in energy efficiency of the good. There is another type of rebound effect, called an indirect rebound effect. The indirect rebound effect refers to the percentage change of energy consumption from other goods and services that is induced by the increased energy efficiency of the regulated good. See Gillingham et al. (2016) for more comprehensive explanation.

major U.S. states (Knittel and Sandler, 2018; Langer et al., 2017) and large-scale surveys such as the National Household Travel Survey (NHTS) (Linn, 2016; Su, 2012).[2] Gillingham (2020) tabulates a long list of relevant studies of this class and reports that the average of the estimated fuel-economy rebound effects is 14%,[3] with a relatively wide range of estimates between 0% and 40%. Small and Van Dender (2007) directly estimate the rebound effects of the CAFE standard using state-level data and report short-run and long-run rebound effects at 4.5% and 22.2%, respectively.

In this paper, we address two important challenges that are unmet in the literature to obtain a more accurate and policy-relevant estimate of the rebound effects of the CAFE standards. First, most of the economic studies estimate the fuel-economy rebound effect by implicitly assuming that the increase in fuel economy is achieved without changing other vehicle attributes. Anderson and Sallee (2016) and West et al. (2017) analytically show that rebound estimates that hold vehicle characteristics constant (henceforth "quality-unadjusted") can overestimate (underestimate) the rebound effects of fuel economy standards when vehicle quality is degraded (improved) for compliance.[4] Gillingham (2020) also emphasizes that conflating fuel-efficiency improvements that materialize exogenously[5] and those that forgo other attributes results in incorrect evaluations of rebound effects. Examining the effect of this trade-off between fuel economy and other vehicle quality on VMT seems more relevant under the new regime of the CAFE standard started in 2012. The new standard imposes increasingly stringent standards every year but instead offers a new "footprint-based" mechanism,[6] which allows more lenient (stringent) standards for large (small) vehicles than the previous

[2]Another focus has been on the the heterogeneity in the VMT elasticity across households: household location types (*i.e.*, road network and population density) (Su, 2012), residential density (Brownstone and Golob, 2009), and nature of vehicle trips (Dillon et al., 2015). Heterogeneity in the VMT elasticity across vehicle types are also estimated (Bento et al., 2009).

[3]He also notes that the average of the rebound estimates in the odometer-reading-based studies is 8.1% and emphasizes that this estimate appears to be more reliable.

[4]West et al. (2017) further show that the extent to which the correlation between fuel economy and other vehicle quality that affects driving patterns and the price range where this trade-off occurs can have an important implication in evaluating the effect of rebound effect.

[5]They refer to this type of energy-efficiency improvements as "zero-cost breakthrough."

[6]Footprint is defined as the rectangular area surrounded by the center of four tires of a vehicle and thus used as one measure of a vehicle's size.

version. This regulatory change was intended to encourage automakers to adopt fuel-saving technologies in increasing fuel economy by preempting their incentives to utilize the trade-off between fuel economy and vehicle size, which was salient before the revision (Klier and Linn, 2012; Knittel, 2011). Anderson and Sallee (2016) suggest that the quality-unadjusted rebound estimates likely overstated the true rebound effect under the previous CAFE standard because such quality adjustments would reduce consumer utility from driving. Under the footprint-based standard, in contrast, they suggest that the quality-unadjusted rebound estimates are more likely to measure the true rebound effect to the extent that the new mechanism neutralizes such incentives. West et al. (2017) provide the first and only empirical causal evidence that quality adjustments offset the rebound effects from improved fuel economy in Texas in 2009 and 2010. Under the footprint-based standard, Leard et al. (2020) conclude that improvements in fuel economy were still achieved mostly by the trade-off between fuel economy and other attributes between 2012 and 2016. Yet, no empirical evidence has been offered about the existence, magnitude, and direction of the quality adjustment in the rebound estimate of the footprint-based CAFE standard.

Second, the estimated VMT elasticity with respect to fuel economy in the literature does not seem to measure the effect of the CAFE standard precisely. This stems from the business practice in the automobile industry that primary vehicle attributes are altered at the timing of remodeling, which usually occurs every four to six years and at different timings for different vehicle models (Klier and Linn, 2016). Then, for example, the vehicle lineup offered in 2014 includes both vehicle models continued since before 2012 without reference to the footprint-based standard and those newly remodeled after 2012 whose attributes are optimized for the new standard. To the extent that the two regimes of the CAFE standard affect the optimal set of vehicle attributes differently, driving behavior would also be affected differently between households owning continued and remodeled vehicles.[7] Therefore, esti-

[7] Unlike gasoline taxes, the CAFE standard does not directly affect households' driving behavior instantaneously at one time. This is also in contrast to the "Cash for Clunkers" program that directly provides financial incentives to consumers so that households would replace fuel-inefficient vehicles with fuel-efficient ones.

mating VMT elasticities with respect to fuel economy by averaging out the vehicle lineup is equivalent to averaging the effects of two different regimes of the CAFE standard. Suppose the new standard increases the sales of fuel-efficient vehicles with milder trade-offs with other vehicle attributes. In that case, such an average elasticity underestimates the rebound effects that are directly attributable to the new CAFE standard. This is especially true in earlier years after new regulatory mechanisms are introduced or when regulatory stringency keeps changing. We address this issue by utilizing the timing of remodeling of each individual vehicle model as a source of variation. This variation enables us not only to estimate the difference in the size of the rebound effect before and after the regulatory change, but also to compare the net fuel-economy rebound effect with and without quality adjustment while circumventing the omitted variable bias.

We estimate the fuel-economy rebound effects in ways that distinguish VMT changes that are attributable to the per-mile cost reduction and bundle quality changes, both of which occur when fuel economy is improved by vehicle remodeling. We take a two-step approach similar to Klier and Linn (2016). First, we estimate the VMT demand function in ways that separately identify the movements along and shifts of the VMT demand curve under fairly plausible assumptions. The movement is identified by the change in gasoline price, and the shift is identified non-parametrically by the vehicle model by model year fixed effects. Then, we estimate how the estimated shift of the VMT demand curve is associated with changes in fuel economy and bundle vehicle quality, and examine whether the relationship differs before and after 2012. We use the 2017 National Household Travel Survey (NHTS), a large-scale survey of nationally representative sample households with ample demographic information. Using the estimated VMT elasticity, we compute the medium-run fuel-economy rebound effect, which applies to the four to six year window and reflects the variation of fuel economy induced by either regime of the CAFE standard.

The results show that the VMT rebound effect with respect to per-mile fuel cost, which corresponds to the movement along the VMT curve, was 8.9% between 2005 and 2016. This rebound estimate is close to the ones obtained in recent studies that use the most reliable odometer reading data. We then find that the vehicle quality adjustment that occurs with vehicle remodeling was as much as 9.2% and completely offset the fuel-cost rebound effect between 2005 and 2011, which corroborates the 0% rebound estimate offered by West et al. (2017). Failing to account for quality adjustments in the rebound estimate resulted in an overestimation by 11.0%-points before 2011. The quality-adjustment effect then reduced to 2.0% after 2012. This attenuation suggests that the fuel efficiency increased with much milder quality adjustment than before, but we still find evidence about overestimation by 3.1%-points after 2012. Furthermore, the differences in the size and direction of the quality adjustment effect strongly suggest that such adjustments were the result of the CAFE standard and its regulatory change in 2012. For trucks, we find that the quality-adjustment effect was almost double that for cars before 2011, but it turned to reinforcing rather than offsetting the fuel-cost rebound effect after 2012. For cars, the quality-adjustment effect still offset the fuel-cost rebound effect after 2012 even though the magnitude was smaller than before. This contrast between cars and trucks before and after 2012 conforms closely to what Anderson and Sallee (2016) and Leard et al. (2020) suggest about the consequences of the regulatory change. That is, automakers were forced to rely more on forgoing vehicle quality for truck fuel economy before 2011 when only the truck standard was raised under the CAFE standard that was disadvantageous to larger trucks. After 2012, in contrast, they benefited from avoiding unnecessary quality adjustments only in trucks under the new footprint-based CAFE standard that was in favor of larger trucks. This is the first empirical evidence that quantifies both the direction and magnitude of the quality-adjustment effect in the rebound estimate, which has been one of the lingering questions. Moreover, our findings highlight the heterogeneity in the effect between cars and trucks. These results contribute to refining the existing rebound estimate and benefit-cost analysis of the footprint-based CAFE standard.

The rest of this paper is organized as follows. Section 2 provides a theoretical framework to explain how changes in fuel economy will shift the VMT demand curve by the trade-off with other vehicle attributes and provides observations about the historical development of some primary vehicle attributes. Section 3 describes our data set, develops our empirical model, and details how we identify the changes in VMT that are associated with changes in vehicle quality. Section 4 reports and interprets the estimation results. Additional tables and figures are presented in the appendices.

2 Conceptual Framework

2.1 Decomposition of Fuel-economy Elasticity of VMT

West et al. (2017) show that VMT elasticity estimates obtained by holding vehicle attributes constant will be biased when changes in fuel economy accompany systematic changes in other vehicle attributes. To reiterate their framework, let $PGAS_i$ and MPG_j denote gasoline prices at household i's location and fuel economy of vehicle j, respectively. Suppose VMT of household i from vehicle j is determined by the cost per mile $C(PGAS_i, MPG_j) = \dfrac{PGAS_i}{MPG_j}$, non-fuel-economy vehicle attributes (X_j), and household demographics (Z_i). Suppose further that X_j is technologically correlated with fuel economy, namely $X_j = X(MPG_j)$. Then, the household's total volume of gasoline consumption on the vehicle can be expressed as

$$QGAS_{ij} = \frac{VMT_{ij}}{MPG_j} = \frac{V\Big(C(PGAS_i, MPG_j), X(MPG_j), Z_i\Big)}{MPG_j}. \tag{1}$$

Taking the natural log of both sides and differentiating with respect to MPG_j yields the elasticity of gasoline consumption with respect to fuel economy as

$$\epsilon_{MPG} = -1 - \eta_C + gal^{-1} \times \frac{\partial V}{\partial X} \times \frac{\partial X}{\partial MPG}. \tag{2}$$

The first term indicates that gasoline consumption decreases by the same percentage as the fuel economy improvement. The second term η_C is the VMT elasticity with respect to the cost per mile at a particular gasoline price (*i.e.*, *ceteris-paribus* rebound effect) and takes negative values. The last product term is referred to as the quality-adjustment term, which measures the portion of the elasticity of gasoline consumption from bundle changes in vehicle attributes that are technologically induced by fuel economy improvements. This product term is most likely to be negative as a whole because fuel economy and other vehicle attributes such as acceleration and size are negatively correlated, whereas such attributes are typically positively correlated with VMT. Therefore, to the extent that the negative correlation between fuel economy and other vehicle attributes is salient, the quality-adjustment term offsets the *ceteris-paribus* rebound effect. If we assume away the correlation between fuel economy and other vehicle attributes, then the quality-adjustment term vanishes. In contrast, taking the natural log and differentiating equation 1 with respect to the gasoline price yields

$$\epsilon_{MPG} = \eta_C, \tag{3}$$

indicating that gasoline consumption decreases at the same rate as VMT decreases following a gasoline price increase.

We now turn to derive econometric implications. Figure 1 shows the stylized (inverse) VMT demand curve that governs the relationship between the cost per mile and VMT as defined in Equation (1). Suppose that only the gasoline price decreases without any change in vehicle attributes. Then, VMT is expected to increase from VMT_0 to VMT_1 along the VMT demand curve ν_0. Next, suppose that the fuel economy of the vehicle increases by reducing its acceleration performance due to the automaker's incapability of introducing cutting-edge fuel-saving technologies. Then, consumers become less willing to drive the car because the decreased acceleration has made it less fun to drive. This response is described as the inward shift of the VMT demand curve from ν^0 to ν^1. Given this inward shift, the VMT increases from VMT_0 only to VMT_1'. If we correctly recognize the quality change and the inward shift of the VMT demand curve, we would observe the inelastic VMT demand curve $\tilde{\nu}$. However, if we estimate the changes in VMT holding other vehicle attributes constant, we estimate the elastic VMT demand curve ν_0. In such a case, we overestimate the true rebound effect with respect to fuel economy. In contrast, if automakers successfully improve fuel economy while enhancing vehicle quality that consumers value, the VMT curve shifts outward and we underestimate the true rebound effects.

Thus, whether and how to control for vehicle attributes in an econometric model can introduce biases in the estimation of the true rebound effect, which in turn results in biased cost and benefit estimates.

2.2 Trade-offs Among Vehicle Attributes, and Timing of the Change

Now we turn to investigating how fuel economy improvements have been offered in the real world, with a special focus on the relationship between other primary vehicle attributes and the timing of the improvements. Figure 2 describes the historical relationship between fuel economy and acceleration performance, measured as the horsepower to weight ratio, for passenger cars and light trucks between 1975 and 2016. For both cars and trucks, we observe that fuel economy increased sharply until the mid 1980s, while acceleration barely increased or slightly decreased. Most recently, after the mid 2000s, fuel economy kept increasing accompanied by increasing acceleration. Only between the mid 1980s and mid 2000s we find fuel economy did not increasing, while we observe a rapid increase in acceleration. This pattern almost perfectly matches the historical development of the Corporate Average Fuel Economy (CAFE) Standards.[8] The CAFE standard was introduced in 1978 and raised sharply until 1985,[9] followed by a two-decade-long lull until the mid to end of the 2000s. The standards have been raised since 2005 for trucks and since 2012 for cars. This apparent coincidence between the CAFE standards, fuel economy, and acceleration suggests that automakers took full advantage of the trade-off between fuel economy and acceleration. That is, when CAFE stringency sharply increased, automakers devoted their resources to improving fuel economy at the cost of acceleration, but once the CAFE stringency stopped

[8] See Figure A.1 in Appendix A

[9] Standards for cars were raised from 18 mpg to 27.5 mpg, a 52% increase, between 1978 and 1985. Standards for trucks were raised from 17.5 mpg to 19.5 mpg between 1982 to 1985.

increasing, they turn to enhancing acceleration at the cost of fuel economy.[10]

Aggregated statistics often exhibit a rather gradual change in fuel economy and other attributes. If we observe individual vehicle models, however, their attributes have evolved discontinuously over time. Figure 3 shows the distribution of year-on-year percentage changes in the four primary vehicle attributes for vehicle models that were continued from the previous year and those remodeled in the year. In either of the attributes, we find greater percentage changes in the years when vehicle models are remodeled. On the other hand, we observe barely discernible percentage changes when vehicle models are continued. This is a well-known business practice in the automobile industry called "remodel cycles", which is typically every four to six years, on average.

These observations suggest that vehicle remodeling is a useful source of variation to identify the relationship between fuel economy and VMT, and that it is essential to appropriately deal with the trade-off between vehicle attributes.

3 Empirical Strategy

3.1 The Data

We use the National Household Travel Survey (NHTS) published in 2017 as the main data set. The NHTS contains demographic information of some 130,000 households along with ownership and usage information of about 240,000 light-duty vehicles and self-reported annual VMT. Each household was surveyed in a month between April 2016 and April 2017. The major benefits of the NHTS are that the households are nationally representative and that an extensive list of demographic information is provided. We use self-reported annual VMT as the dependent variable. We acknowledge that self-reported VMT is a less accurate measure of true VMT than odometer-reading-based VMT due to potential errors in estimating and reporting VMT. However, Li et al. (2014) and Linn (2016) conclude that such errors do not necessarily introduce biases in one direction or the other, on average, and yield

[10] See Figure A.2 for the trade-off between fuel economy, horsepower, and curb weight. We see clearer trade-offs between them.

broadly similar results. The NHTS also provides "Estimated VMT," which is calculated based on a combination of the agency's simple econometric models. This version of VMT is attractive in that it increases the number of observations available for estimation, but we prefer not to use this version of VMT since we are not confident enough about the direction and magnitude of the subsumed estimation errors in each step. We omit vehicle models older than 12 years old, which were produced before 2005. Although this omission results in a 30% loss of observation, we do so because vehicles that are too old may not be immediately capable of driving with valid registration and the operation of such old vehicles may be determined beyond economic theory. We choose the 12-year-old criterion because the U.S. Bureau of Transportation Statistics reports that the average age of light-duty vehicles "in operation" in 2017 was 11.2 years old. We also omit observations with missing data for either of the variables we use in our estimation. Although we lose more observations, we would rather gain unbiasedness than gain efficiency of our estimates. As a result, we are left with some 110,000 observations of vehicles.

Since one of our primary interests is the VMT elasticity with respect to gasoline prices, we need to have sufficient meaningful identifying variation in gasoline prices. Due to confidentiality, the NHTS provides only annual average gasoline prices that vary only across 102 distinct regions.[11] Instead, we use quarterly gasoline prices obtained from the Cost of Living Index (COLI) by the Council for Community and Economic Research[12] of the American Chamber of Commerce for some 270 Combined Core-Based Statistical Areas (CBSAs). For the anonymized regions in the NHTS, we impute quarterly gasoline prices as follows. First, we obtain monthly gasoline prices from the Energy Information Agency (EIA) at the PADD level and compute the quarterly average gasoline prices in each PADD. We also compute the average quarterly gasoline prices for each CBSAs. Then, we compute deviations between the COLI-based and EIA-based gasoline prices and impute the quarterly gasoline prices for the

[11] Fifty-two Combined Core-Based Statistical Areas (CBSAs) with more than 1 million population are specified and the remaining areas are anonymized and subsumed at the state level.

[12] Previously known as the American Chamber of Commerce Research Association (ACCRA).

anonymized regions.[13] As a result, we have 252 distinct regions (52 major CBSAs plus 200 small ones) over four quarters from the second quarter of 2016.

Other relevant vehicle attributes, including model generation, are obtained from Ward's Automotive Yearbook. Since the NHTS data set specifies vehicles only at the vehicle model level (rather than the vehicle trim level), we merge the vehicle attributes of "base grade" within each vehicle model and model year. Table 1 tabulates the summary statistics of the main variables.

3.2 The Empirical Model

3.2.1 Estimating VMT Demand Curve (1st Step)

We now estimate how households' annual vehicle miles traveled (VMT) is associated with changes in fuel economy through two channels: per-mile fuel cost and vehicle quality. In the literature that uses household-level data, variants of the following Cobb-Douglas VMT function have been widely estimated:

$$\log(VMT_{ij}) = \beta_0 + \beta_1 \log(FCOST_{ij}) + \boldsymbol{x}_j^{'}\boldsymbol{\gamma} + \boldsymbol{z}_i^{'}\boldsymbol{\phi} + \varepsilon_{ij}, \tag{4}$$

where i indexes households and j indexes vehicles. $FCOST_{ij}$ denotes the fuel cost of vehicle j that household i owns, in terms of either gasoline prices that household i faces, fuel economy of vehicle model j, or the ratio of the two, which is per-mile fuel cost. $\boldsymbol{x}_j$ and $\boldsymbol{z}_i$ are the vectors of vehicle attributes and household characteristics, respectively, and can be replaced with vehicle and household fixed effects depending on the data structure. The β_1 should of primary interest, which shows the VMT elasticity of fuel costs. This specification, however, suffers from a dilemma. Adding $\boldsymbol{x}_j$ means that the β_1 is identified as a fuel-cost VMT elasticity holding vehicle attributes constant, which precludes the effect of vehicle quality

[13] This is similar to the approach by Linn (2016). Another example is Banzhaf and Kasim (2019) , who regress COLI gasoline prices on those of NHTS and use the predicted values. However, Banzhaf and Kasim (2019) uses confidential NHTS data and identify the household location at the zip code level, which is not applicable in our analysis.

changes accompanied by the change in fuel economy. Removing or reducing $\boldsymbol{x}_j$ triggers identification issues pertaining to omitted variable biases.

To distinguish the movement along and the shift of the VMT demand curve, we take a two-step approach similar to Klier and Linn (2016) and Knittel (2011), who identify the shift of the technology trade-off curve between fuel economy and other attributes as the year or year by vehicle model dummy variables. We isolate the portion of VMT that is attributable to vehicle attributes using vehicle model by model year fixed effects. In the first step, we estimate the following Cobb-Douglas VMT demand function by Ordinary Least Squares (OLS):

$$\log(VMT_{id,jt}) = \beta_0 + \beta_1 \log(GASP_i) + \beta_2 \log(\overline{DPM}_{ij}) + \xi_{jt} + \phi(i, d, j) + \tau_q + \varepsilon_{id,jt}, \quad (5)$$

where i indexes households, j vehicles, d primary drivers of vehicle j, q survey quarter, and t vehicle model year.[14] $VMT_{idq,jt}$ is the self-reported annual VMT of vehicle j produced in year t that household i owns (in survey quarter q)[15] whose primary driver is reported as person d. $GASP_i$ is the average retail gasoline price that household i faces (in surveyed quarter q).

Following Linn (2016), we add $\overline{DPM}_{ij}$, the natural log of the average dollar per mile of other vehicles within a household that owns multiple light-duty vehicles. This is defined as the ratio of gasoline prices in the surveyed quarter to the average fuel economy of other vehicles within the same household. To single-vehicle households, a value of zero is assigned. We add this variable for two reasons. First, $\overline{DPM}_{ij}$ is expected to account for within-household substitution effects for multi-vehicle households. As Linn (2016) points out, it seems plausible to regard the decision about VMT on each vehicle as part of a problem of allocating household VMT to each vehicle they own, such as a combination of a minivan

[14] Note that index t is one of the vehicle attributes and not the time dimension of the variables. However, we will recover the time dimension of vehicle attributes later so we show t separated by comma in equation (5).

[15] Since all vehicles within a household are surveyed in the same survey quarter, there is no variation over survey quarters within a household. Therefore, the index i suffices.

for leisure and a sedan for commuting. Then, changes in "relative" driving costs, due either to changes in gasoline price or fuel economy, will encourage the household to drive more on one vehicle and less on the other. Second, $\overline{DPM}_{ij}$ virtually generates variation in $GASP_i$ over j within a household. If the substitution exists, the VMT responds to changes in the driving cost differently across vehicles even at the same gas price. Given the relatively limited variation in gas prices in our data, we expect that the within-household variation increases the identifying power of $GASP_i$. In equation (5), β_1 and β_2 exhibit the VMT elasticity with respect to fuel price without the within-household substitution effect and the substitution effect for multi-vehicle households, respectively. β_1 is expected to be negative and β_2 is expected to be positive. The economy-wide average VMT elasticity with respect to fuel economy is then calculated by $\widehat{\beta}^* = \widehat{\beta}_1 + 0.539 \times \widehat{\beta}_2$, where 0.539 is the average share of multi-vehicle households in our data during our sample period.

The key to identifying the fuel-cost VMT elasticity and the VMT change caused by vehicle quality change is the vehicle model by model-year fixed effect $\xi_{j,t}$. This term captures any time-varying vehicle-model specific VMT and serves as a vehicle quality index measured as the (natural log of) VMT. Since $\xi_{j,t}$ absorbs all the vehicle quality, β_1 identifies the average VMT elasticity with respect to fuel cost that is independent of the vehicle attributes of any vehicle model and model year. We estimated the effect of changes in vehicle quality on the VMT using $\xi_{j,t}$ in the second step.

The benefit of using the NHTS is the abundance of household demographic information. By $\phi(i, d, j)$ we control for an extensive list of household demographics. For example, we control for household income category, state, size, number of children under age 16. We also control for age/race/sex/education of the primary driver of each vehicle. Additionally, we include sets of triple interactions between vehicle class, brands, and such household characteristics as vehicle count, income group, number of children under age 16. These triple interactions account for any heterogeneous correlation between household characteristics and their choice of vehicles over vehicle classes such as SUV and over brands such as Cadillac.[16] Finally, τ_q is the survey quarter fixed effects to account for seasonal factors that affect all the surveyed households in the same way in each quarter.

With the above identification of the VMT demand function, we implicitly make the following conceptual and econometric assumptions, which we believe to be reasonably plausible in our setting. First, VMT responds to changes in cost per mile by the same magnitude regardless of whether the changes stem from gasoline prices and fuel economy. Although studies do not unanimously agree with the validity of this assumption,[17] careful examination by Linn (2016), whose data and framework have much in common with ours, finds it ambiguous but the magnitude is small enough to make the difference statistically distinguishable. Second, changes in fuel economy almost always accompany changes in other vehicle attributes that consumers value in their decision on driving mileage. This is consistent with our finding in Section 2.2 that major performance-related vehicle attributes vary almost exclusively at the timing of vehicle remodeling. Third, gasoline prices are exogenous to the individual VMT decision. This assumption is commonly supported in the relevant literature that uses micro-data (Gillingham et al., 2015; Knittel and Sandler, 2018). Fourth, the relationship between VMT and gasoline prices is governed by the Cobb-Douglas functional form with a set of fixed effects. Gillingham and Munk-Nielsen (2019) conclude that the log-log functional form is approximately linear over a broad range of gasoline prices. Moreover, Gillingham et al. (2015) and Gillingham and Munk-Nielsen (2019) prefer the log-log functional form over other semi- or non-parametric specifications, emphasizing that the vehicle model fixed effect is the key to identifying the VMT elasticity.

[16] In our setting, adding household fixed effects is not appropriate because it completely absorbs the variation in gas prices.

[17] Greene et al. (1999) and Frondel et al. (2012) conclude that there is no statistically significant difference in the VMT elasticity between gasoline price and fuel economy, but Gillingham et al. (2012) finds that VMT responds more to gasoline prices than fuel economy.

3.2.2 Estimating Shift of VMT by Vehicle Quality Adjustment (2nd Step)

In the second step, we investigate how much of the estimated quality-index VMT is attributable to the bundle changes in vehicle attributes before and after 2012, when the footprint-based CAFE standard was introduced. To do so, we take out $\widehat{\xi}_{j,t}$ from the estimation of equation (5), and then estimate the following specification by OLS:

$$\begin{aligned}\widehat{\xi}_{jt} = \delta_0 + \delta_1 \log(MPG_{jt}) + \delta_2 \log(MPG_{jt}) \times After_t \\ + \delta_3 GEN_{jt} + \delta_4 GEN_{jt} \times AFTER_t + \theta_j + \tau_t + \epsilon_{jt}.\end{aligned} \tag{6}$$

MPG_{jt} is the fuel economy of vehicle model j of model year t. $After_t$ takes the value of unity if the vehicle model is offered after 2012, and captures the difference in the average bundle quality that is not technologically related to fuel economy. GEN_{jt} is the model generation of vehicle model j in year t, which increases in years when the vehicle model is remodeled. It shows the average changes in bundle quality of vehicles at the timing of remodeling. θ_j is the vehicle model fixed effect that accounts for time-invariant vehicle model-specific quality that is correlated with VMT. Note that τ_t plays a different role than what the typical time fixed effect does. That is, it absorbs a systematic difference in VMT associated with the vintage of vehicles. It is reported in the NHTS that annual VMT almost linearly decreases with vehicle age. Although we remain agnostic about the underlying mechanism of this vintage effect, τ_t absorbs such systematic changes in VMT along vehicle age.

After all, δ_1 is identified by the correlation between changes in fuel economy and changes in quality-index VMT at the timing of remodeling before 2011 within the same vehicle model. The identifying variation is, for example, the difference in fuel economy between Ford F-150 of kth generation and its $k+1$th generation before 2011. δ_3 is identified by the correlation between the average changes in the bundle vehicle quality other than fuel economy between generations of a vehicle and the change is VMT before 2011. δ_2 and δ_4 indicate the difference in the extent of the correlations referenced in δ_1 and δ_3 after 2012.

We also estimate the following specification that is augmented with vehicle attributes X_{jt} that are observed and technologically correlated with fuel economy:

$$\begin{aligned}\widehat{\xi}_{jt} = \widetilde{\delta}_0 + \widetilde{\delta}_1 \log(MPG_{jt}) + \widetilde{\delta}_2 \log(MPG_{jt}) \times AFTER_t + X_{jt}'\widetilde{\boldsymbol{\delta}} \\ + \widetilde{\delta}_3 GEN_{jt} + \widetilde{\delta}_4 GEN_{jt} \times AFTER_t + \theta_j + \tau_t + \epsilon_{jt}.\end{aligned} \tag{7}$$

X_{jt} includes the natural log of horsepower, curb weight,[18] and torque, and each variable is also interacted with $AFTER_t$.[19] It is widely known that these vehicle attributes are highly negatively correlated with fuel economy (Knittel, 2011; Klier and Linn, 2016). This strong negative correlation enables us to derive different implications for the effect of fuel economy on the shift of VMT between specifications (6) and (7). In specification (6), MPG_{jt} implicitly involves the technological trade-off between horsepower, curb weight, and torque to the extent that they explain the variation in MPG_{jt}. Importantly, the remaining variation in MPG_{jt} is absorbed by GEN_{jt} rather than by ϵ_{jt} because vehicle attributes are updated when vehicles are remodeled,[20] that is, when GEN_{jt} increases. Therefore, MPG_{jt} and GEN_{jt} jointly suffice to explain almost all bundle changes in vehicle quality when vehicle j is remodeled. Accordingly, δ_2 and δ_3 are interpreted as the VMT elasticity with respect to fuel economy that with forgone horsepower, curb weight, and torque. In contrast, specification (7) includes all these variables, suggesting that MPG_{jt} should be interpreted as the change in fuel economy holding horsepower, curb weight, and torque constant. Such fuel economy improvements are achieved through advances in fuel-saving technologies. GEN_{jt} absorbs bundle quality changes pertaining to this remodeling that are irrelevant to fuel economy, horsepower, curb weight, and torque, which can be thought of as luxury and comfort features.

Turning to economic interpretation, our main question is to identify the difference in the rebound effects depending on whether to account for vehicle quality adjustments. This

[18] A measure of vehicle weight with a full tank of fuel and other necessary fluids without passengers and cargo loaded.

[19] Interaction terms are omitted in Equation (7) for notational brevity.

[20] Although MPG is indexed by t and g, the variation is dominated by generation.

gap appears through the difference in how we control vehicle attributes in our econometric model. The quality-unadjusted elasticity of VMT shift is identified only by the coefficients on $\log(MPG)$ in Equation (9): $\widetilde{\delta}_1$ before 2011 and $\widehat{\widehat{\delta}}_1 + \widehat{\widehat{\delta}}_2$ after 2012. The elasticity of VMT shift that accounts for the quality trade-off is identified by all $\widehat{\delta}$s in Equation (7): $\widehat{\delta}_1 + \widehat{\delta}_3$ before 2011 and $\widehat{\delta}_1 + \widehat{\delta}_2 + \widehat{\delta}_3 + \widehat{\delta}_4$ after 2012. This summation is valid because almost all vehicle qualities, including fuel economy and other unobserved vehicle attributes, are to change with remodeling. Since $\widehat{\delta}$s and $\widehat{\widehat{\delta}}$s are the percentage change in the "shift" of VMT with respect to a percentage change in fuel economy, we need to translate it into the percentage change in VMT. We approximate this by using the average percentage change in the shift of VMT for both periods. Adding the fuel cost rebound effect $\widehat{\beta}^*$, the total fuel-economy elasticity of the VMT shift before 2011 is defined as follows:

$$\begin{cases} \widehat{\widehat{\eta}}_{2011} & = \widehat{\beta}^* + \overline{\Delta VMT}_{\%,\xi,2011} \times \widehat{\widehat{\delta}}_1 \\ \widehat{\eta}_{2011} & = \widehat{\beta}^* + \overline{\Delta VMT}_{\%,\xi,2011} \times (\widehat{\delta}_1 + \widehat{\delta}_3) \end{cases}, \tag{8}$$

where $\widehat{\widehat{\eta}}$ is quality unadjusted and $\widehat{\eta}$ is quality adjusted. $\overline{\Delta VMT}_{\%,\xi,2011}$ denotes the average percentage shift in the quality index VMT between 2005 and 2011. Those after 2012 are calculated by

$$\begin{cases} \widehat{\widehat{\eta}}_{2012} & = \widehat{\beta}^* + \overline{\Delta VMT}_{\%,\xi,2012} \times (\widehat{\widehat{\delta}}_1 + \widehat{\widehat{\delta}}_2) \\ \widehat{\eta}_{2012} & = \widehat{\beta}^* + \overline{\Delta VMT}_{\%,\xi,2012} \times (\widehat{\delta}_1 + \widehat{\delta}_2 + \widehat{\delta}_3 + \widehat{\delta}_4) \end{cases}. \tag{9}$$

4 Empirical Results

4.1 Fuel-cost Elasticity of VMT

We estimate Equation (5) by OLS and tabulate the results in Table 2. The four specifications are differentiated by the set of fixed effects. Specification (1) includes only survey quarter fixed effects and vehicle model by model year fixed effects. Specification (2) is augmented by household demographics fixed effects. Specification (3) further includes fixed effects that control for the demographic characteristics of the primary driver of each vehicle. Finally, Specification (4) includes all sets of fixed effects. Economic theory predicts that $\widehat{\beta}_1$ is negative and $\widehat{\beta}_2$ is positive. Specification (1) yields an irrational sign on $\widehat{\beta}_2$. This is rather predicted because household demographic characteristics are likely to be correlated with households' vehicle portfolio. The other specifications yield point estimates that are of broadly similar magnitude and consistent sign, among which Specification (4) is our most preferable one. Interpreting the coefficients, we find that a one percent increase in the fuel cost is associated with a 0.175 percent reduction in the annual VMT of a vehicle. However, households owning multiple vehicles will increase VMT from other vehicles by 0.16 percent. Using the average share of multi-vehicle households, which is 0.539, we obtain the economy-wide average VMT elasticity at 0.089. This is translated as a 8.9% fuel-cost rebound effect. This 8.9% rebound effect is within the range of estimates obtained by reliable studies, which is between 0% and 40%. Moreover, this is close to the central estimate among the studies that use vehicle-level odometer reading.

Another result of interest in this estimation is $\widehat{\xi}_{jt}$, which is the vehicle model by model year fixed effect. This fixed effect nonparametrically captures the vehicle model and model year specific VMT (in terms of natural log: call "quality-VMT") that is attributable to the bundle vehicle quality in terms of deviations from the overall average. Figure 4 shows the distribution of this quality-VMT each year for passenger cars and light trucks. For both vehicle categories, the quality-VMT has been gradually increasing over time, with at a slightly higher rate between 2012 and 2015. The average cumulative increase between 2005 and 2016 is 2,107 miles for passenger cars and 4,391 miles for light trucks.

4.2 Shift of the VMT Demand Curve and Vehicle Quality Adjustment

Observations in Section 2.2 and empirical evidence in the previous subsection jointly suggest that the VMT demand curve has gradually shifted outward since around the mid 2000's. Our next step is to examine whether and how changes in fuel economy have contributed to the outward shift of the VMT demand curve through bundle changes in other vehicle quality.

Table 3 tabulates the estimation results of Equations (6) and (7) by OLS and groups them into (I) and (II). Each group offers the results from total observations as well as from the subsamples of passenger cars and light trucks. Both specification groups include vehicle model and model year fixed effects, but they are differentiated such that group (II) includes the natural log of horsepower, curb weight, and torque. By this differentiation, coefficients on $\log(MPG)$ in group (I) show the percentage change in the quality-VMT associated with a one percent increase in fuel economy that entails an adjustment of vehicle quality to the extent that the vehicle quality and fuel economy are correlated. GEN absorbs any other forgone vehicle quality. Coefficients on $\log(MPG)$ in group (II) show the percentage change in the quality-VMT associated with a one percent increase in fuel economy, holding horsepower, curb weight, and torque constant. Therefore, such gains in fuel economy can be thought of as the result of technology progress without adjusting such primary vehicle attributes.

Interpreting the results in group (I), a one percent increase in fuel economy is associated with a 0.46 percent increase in the quality-VMT on average between 2005 and 2012, and the magnitude is greater for passenger cars (0.62%) than light trucks (0.2%). This association becomes weak after 2012 by 0.7%-point, and passenger cars exhibit a greater reduction than light trucks. In terms of other vehicle quality, every vehicle remodeling is associated with a 2.7% decrease in the quality-VMT on average between 2005 and 2011, and the magnitude is greater for passenger cars (-3.2%) than light trucks (-2.2%). After 2012, the reduction becomes milder by 1%-point to 2%-points.

The results in group (II) show the changes in quality-VMT associated with a one percent increase in fuel economy and one remodelling cycle, while holding horsepower, curb weight, and torque constant. We obtain the opposite implication for passenger cars and light trucks. For cars, a one percent increase in fuel economy is associated with a 0.8% increase in quality-VMT between 2005 and 2011 and the increase will decline by 0.21%-point after 2012. In contrast, a one percent increase in fuel economy for light trucks is associated with a 0.08% decrease in quality-VMT between 2005 and 2011, but the association turns to positive after

2012. Remodeling is now associated with a substantially greater increase in the quality-VMT than in group (I). This is primarily because GEN in group (II) is absolved of the quality loss that would have incurred when vehicle quality was adjusted.

4.3 Medium-run Fuel Economy Rebound Effect

In this section, we estimate the fuel economy rebound effects for passenger cars and light trucks in each period. More specifically, our rebound estimates are regarded as a medium-run effect since the elasticity is identified by the quality change at vehicle remodeling, which occurs every four to six years. We provide both quality-adjusted and unadjusted fuel economy rebound effects and derive implications for the effect of the regulatory change in the CAFE standard.

Table 4 tabulates the rebound effects for passenger cars and light trucks, both before 2011 and after 2012. Column (a) shows the fuel cost rebound effects estimated in the first step. Columns (b) and (d) show the fuel economy rebound effects through the shift of the VMT curve, with values in column (b) adjusted for the quality trade-off and (d) unadjusted. Column (c) shows our best-guess estimates about the fuel economy rebound effects that are expected to manifest over four to six years.

The numbers in column (b) show that the quality-adjustment effect was so large between 2005 and 2011 that it completely offset the fuel-cost rebound effect. The net fuel economy rebound effect was -0.3% economywide, suggesting that a one percent increase in fuel economy will result in 0.3% extra fuel consumption savings. Especially, the quality adjustment was substantially large for light trucks, nearly double that of passenger cars. However, after 2012, the quality-adjustment effect diminished. Now light trucks exhibit a positive quality-adjustment effect by 0.7%, resulting in the net fuel economy rebound effect of 9.6%, suggesting that the expected fuel savings will be canceled by 8.9% through financial benefit from reduced driving costs and by 0.7% by the quality change making it more fun to drive trucks.

Column (e) shows the quality-unadjusted rebound estimates, which are typically offered in the economic literature. Since fuel economy improvements with horsepower, curb weight, and torque being maintained at the same level appear to mean a pure quality improvement, the quality effects are mostly positive. Then, the quality-unadjusted net rebound effects are around 10%. Column (f) offers the difference between the two net fuel economy rebound effects, and positive values mean that the quality-unadjusted rebound estimates overestimate the true rebound effect. We find that failing to account for the quality-adjustment effect resulted in an overestimation of the true fuel economy rebound effect by 11.0%-points between 2005 and 2011 and by 3.1%-points after 2012.

The strong quality-adjustment effect between 2005 and 2011 reinforces the causal evidence offered by West et al. (2017) that the quality adjustment completely offset fuel-cost rebound effects in Texas 2009 and 2010. Our results provide new empirical evidence that the effect attenuated but not completely vanished between 2012 and 2016. This lingering quality-adjustment effect after 2012 is in line with Leard et al. (2020), who find automakers increased fuel economy by exploiting quality trade-offs. The remarkable heterogeneity in the effect between cars and trucks is also consistent with what Anderson and Sallee (2016) suggest about the consequences of the regulatory change. Truck standards began sharply increasing in 2005 (Figure A.1 in Appendix A), when the CAFE standard was disadvantageous to larger vehicles. Therefore, automakers were more likely to rely on the quality trade-off to squeeze fuel economy improvements during the period. In contrast, since the new footprint-based CAFE standard is designed in favor of larger vehicles, it seems plausible that automakers benefit from avoiding quality trade-offs when remodeling vehicles.

5 Conclusion

The size of the rebound effect is one of the key elements in evaluating the effectiveness and cost and benefit of energy-efficiency standards. An extensive list of studies have provided rebound estimates, however, economists have yet to find common ground on the true rebound effect. This paper contributes to the literature by providing new empirical evidence that addresses two challenges in estimating fuel economy rebound effects. First, we separately identify the fuel-economy rebound effects caused by a decrease in per-mile fuel cost and by forgone vehicle quality. Second, we estimate the difference in the fuel economy rebound effects before and after 2012 and offer implications for the possible effects of the new footprint-based CAFE standard on the rebound effect.

We estimate a VMT demand function using the 2017 NHTS data set with some 110,000 vehicles representative of U.S. population. We identify the two rebound effects by taking a two-step approach and utilizing vehicle remodeling cycles as a new source of variation. The results show that the VMT rebound effect with respect to per-mile fuel cost, which corresponds to the movement along the VMT curve, was 8.9% between 2005 and 2016. We then find that the vehicle quality adjustment that occurs with vehicle remodeling was as much as 9.2% and completely offset the fuel-cost rebound effect between 2005 and 2011, which corroborates the 0% rebound estimate offered by West et al. (2017). Failing to account for quality adjustments in the rebound estimate resulted in an overestimation by 11.0%-points before 2011. The quality-adjustment effect then reduced to 2.0% after 2012. This attenuation suggests that the fuel efficiency increased with much milder quality adjustment than before, but we still find evidence about overestimation by 3.1%-points after 2012.

Two policy implications are immediately derived from our results. First, it is likely that the 10% rebound effect on which most economists have agreed still appears to be slightly overstating the fuel-economy rebound effect under the footprint-based CAFE standard. Second, the footprint-based standard for trucks are too lenient in the sense that it is enhancing the fuel-economy rebound effect. In a more general sense, the heterogeneity in the quality-adjustment effect suggests that regulatory authorities should carefully evaluate the possible effects of quality changes on rebound effects when energy-efficiency standards are likely to affect primary product attributes.

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Table 1: Summary Statistics

	N.Obs.	Mean	SD	Min	Max
Annual VMT (miles/year)	141,536	11,124.91	12,413.55	1	200,000
Fuel Cost ($/gallon equivalent)	190,847	2.41	0.30	2.13	9.86
Fuel Economy (miles/gallon)	191,677	31.94	10.60	8.56	176.92
Per-mile Cost ($/mile)	190,847	0.155	0.031	0.020	0.476
Avg. Per-mile Cost of Other Vehicles ($/mile)	155,318	0.120	0.030	0	0.431
Number of Household Members	191,677	2.44	1.22	1	13
Number of Drivers per Household	191,677	1.98	0.77	0	9
Number of Light-duty Vehicles per Household	191,677	2.48	1.25	1	12

Table 2: VMT Demand Function (1st Step)

	(1)	(2)	(3)	(4)
$\widehat{\beta}_1$: $\log(GASP)$	-0.187***	-0.184**	-0.185**	-0.175***
	(0.0245)	(0.0695)	(0.0738)	(0.0628)
$\widehat{\beta}_2$: $\log(\overline{DPM})$	-0.0256***	0.149***	0.162***	0.160***
	(0.00255)	(0.0133)	(0.0145)	(0.00938)
$\widehat{\beta}^*$: Fuel-cost Elasticity	0.201	0.105	0.098	0.089
Survey Quarter FE	Y	Y	Y	Y
Model $\times$ Model year FE (ξ_{jt})	Y	Y	Y	Y
Household Demographics FE	N	Y	Y	Y
Primary Driver Demographics FE	N	N	Y	Y
Household Demographics $\times$ Vehicle Class $\times$ Brand FE	N	N	N	Y
N	110,667	110,571	110,516	109,649
adj. R^2	0.051	0.138	0.154	0.176

(Notes) Estimated by OLS. Dependent variable is $\log(VMT)$. Standard errors in parentheses (clustered by CBSA). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: VMT Shift by MPG and Vehicle Remodeling (2nd Step)

	(I) Vehicle Quality Adjusted ($\widehat{\delta}$)			(II) Not Quality Adjusted ($\widehat{\widehat{\delta}}$)		
	All	Car	Truck	All	Car	Truck
	(1)	(2)	(3)	(4)	(5)	(6)
δ_1: $\log(MPG)$	0.460***	0.624***	0.198***	0.449***	0.797***	-0.0783***
	(0.0138)	(0.0263)	(0.0156)	(0.0165)	(0.0318)	(0.0252)
δ_2: $\log(MPG) \times AFTER$	-0.0706***	-0.0565***	-0.00825	0.00488	-0.208***	0.406***
	(0.00462)	(0.00743)	(0.00946)	(0.00832)	(0.0120)	(0.0228)
δ_3: GEN	-0.0272***	-0.0323***	-0.0215***	0.543***	0.476***	0.886***
	(0.00178)	(0.00303)	(0.00213)	(0.0415)	(0.119)	(0.0770)
δ_4: $GEN \times AFTER$	0.0154***	0.0103***	0.0217***	0.206***	0.558***	0.106
	(0.000327)	(0.000650)	(0.000400)	(0.0337)	(0.0675)	(0.0770)
Model FE	Y	Y	Y	Y	Y	Y
Model Year FE	Y	Y	Y	Y	Y	Y
Performance Attributes (X)	N	N	N	Y	Y	Y
N	109,647	51,797	57,850	109,647	51,797	57,850
adj. R^2	0.723	0.686	0.775	0.727	0.695	0.787

(Notes) Standard errors in parentheses (clustered by brand). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Quality Adjusted Fuel Economy Rebound Effects

	Period	Fuel Cost RE (a)	(I) Vehicle Quality Adjusted		(II) Not Quality Adjusted		Difference
			Quality RE (b)	Total RE $(c) = (a) + (b)$	Quality RE (d)	Total RE $(e) = (a) + (d)$	$(f) = (e) - (c)$
Car	2005 - 2011	8.9%	-5.6%	3.3%	1.7%	10.6%	7.3%pt
	2012 - 2016		-2.1%	6.7%	0.8%	9.6%	2.9%pt
Truck	2005 - 2011	8.9%	-10.6%	-1.7%	-0.4%	8.5%	10.2%pt
	2012 - 2016		0.7%	9.6%	1.1%	10.0%	0.4%pt
All	2005 - 2011	8.9%	-9.2%	-0.3%	1.8%	10.7%	11.0%pt
	2012 - 2016		-2.0%	6.9%	1.1%	10.0%	3.1%pt

(Notes)

Figure 1: Decomposing the Change in VMT from Increased Fuel Economy

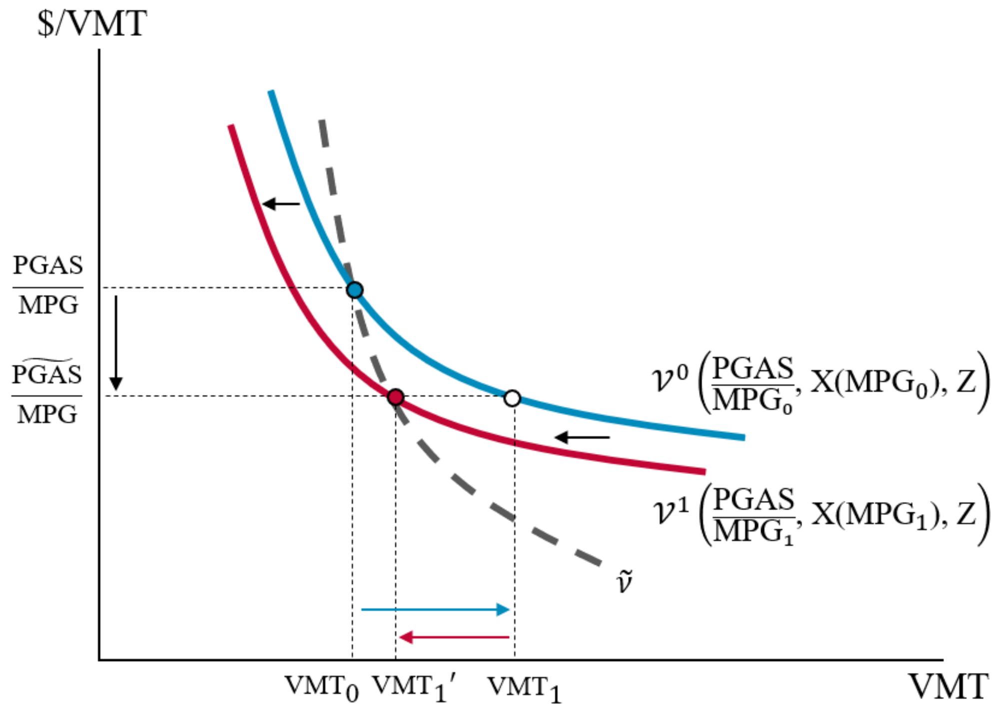
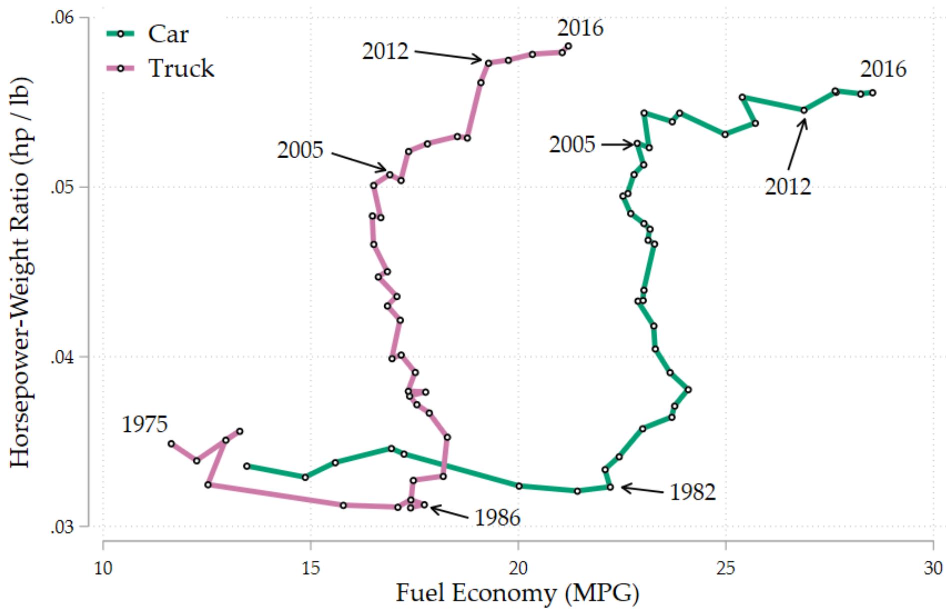
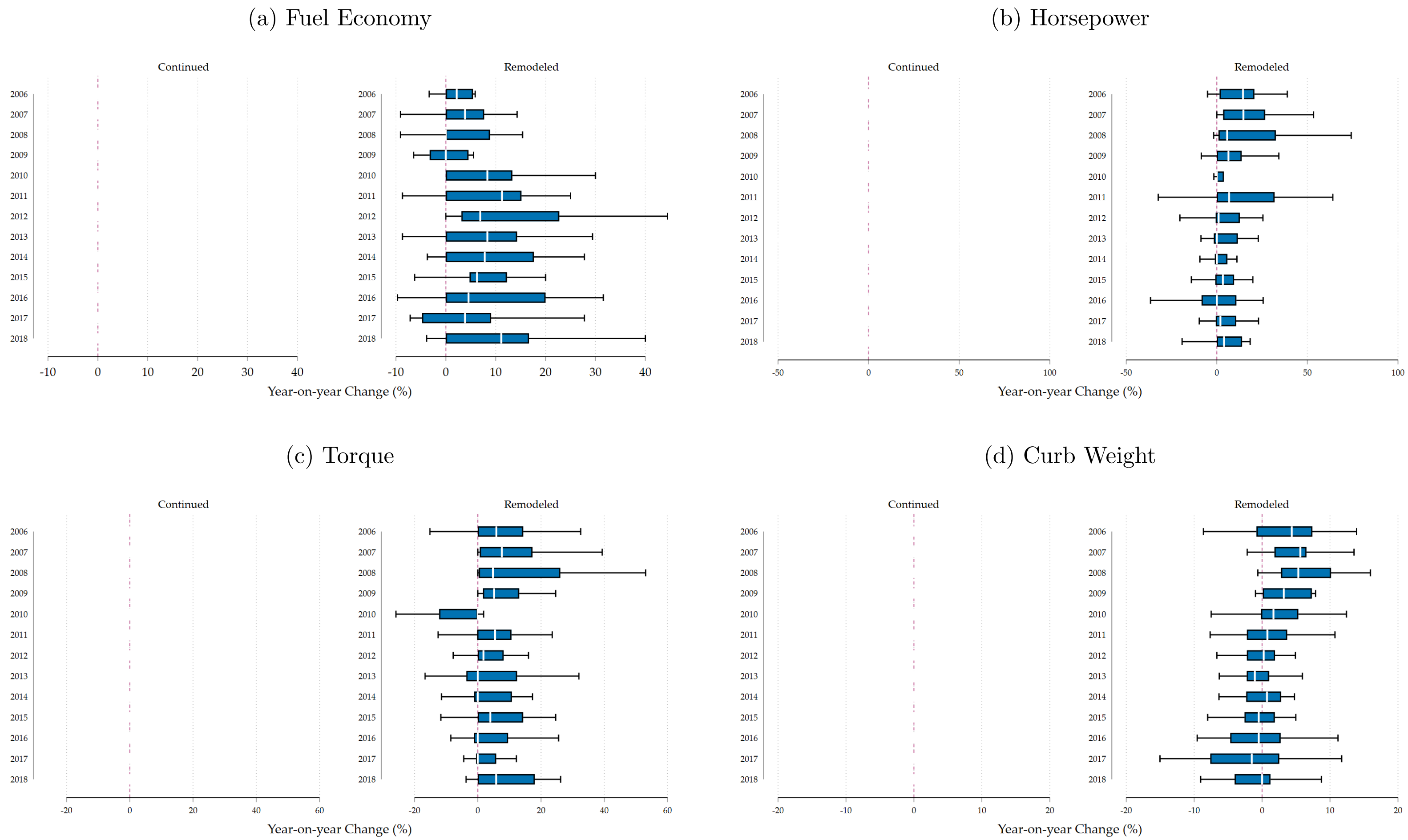


Figure 2: Trade-off between Fuel Economy and Acceleration Performance



(Notes) This figure plots and connects the pairs of average fuel economy and average acceleration (measured as the ratio of horsepower to curb weight) for Cars and Light trucks between 1975 and 2016. Horizontal (vertical) movements indicate an improvement in fuel economy (acceleration).

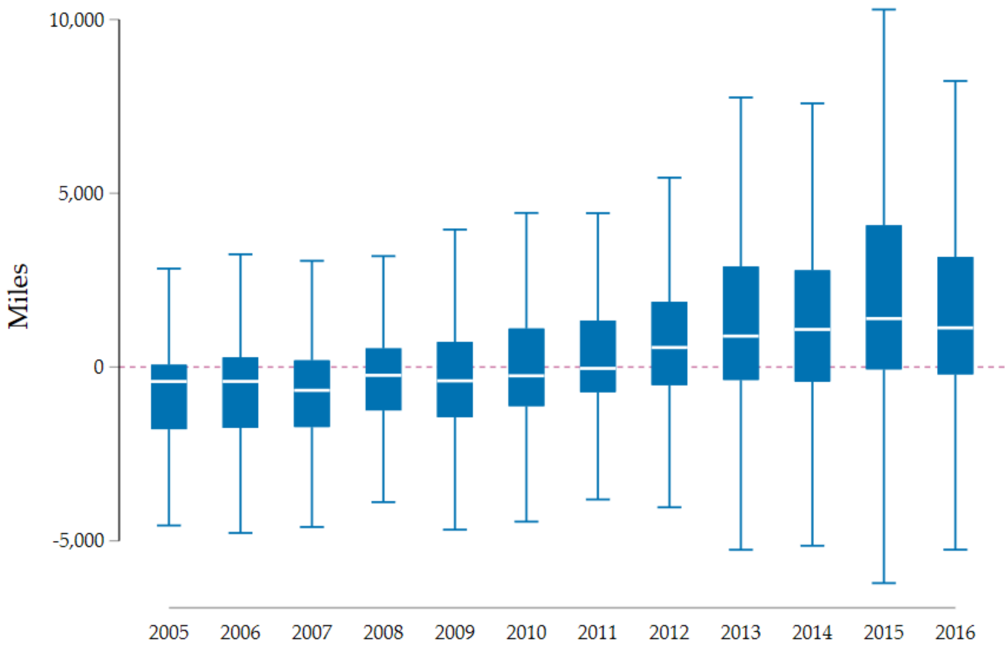
Figure 3: % Year-on-year Change in Vehicle Attributes for Continued and Remodeled Vehicles



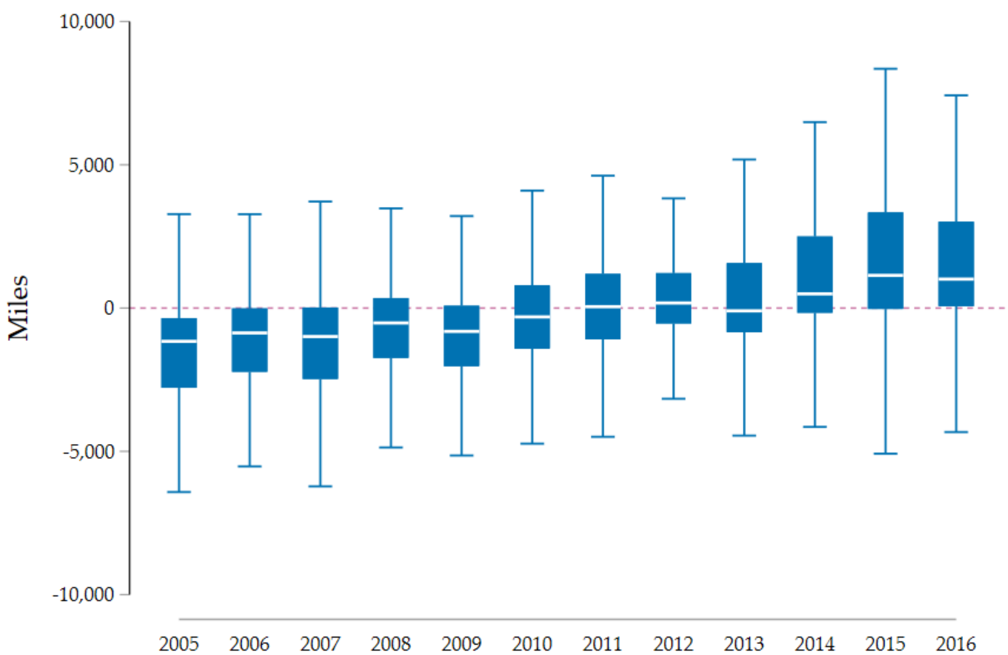
(Notes) Each figure shows the box plot of year-on-year % changes in each of the vehicle attributes for vehicle models that were continued from previous years and those that newly remodeled.

Figure 4: Yearly Distribution of Vehicle Quality Index in VMT

(a) Passenger Car



(b) Light Trucks



(Notes)

Appendix A Supplemental Figures

Figure A.1: Historical Development of the CAFE Standard

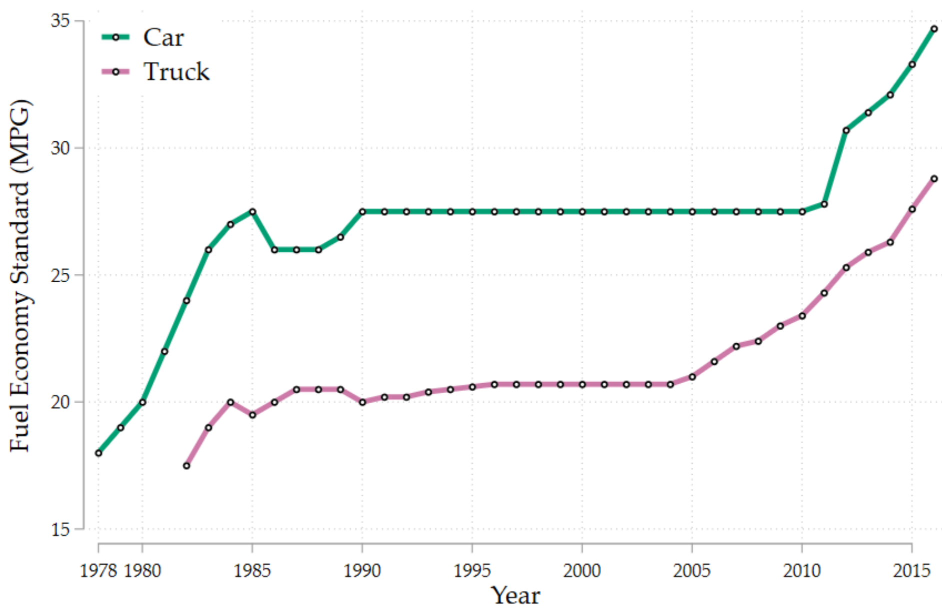
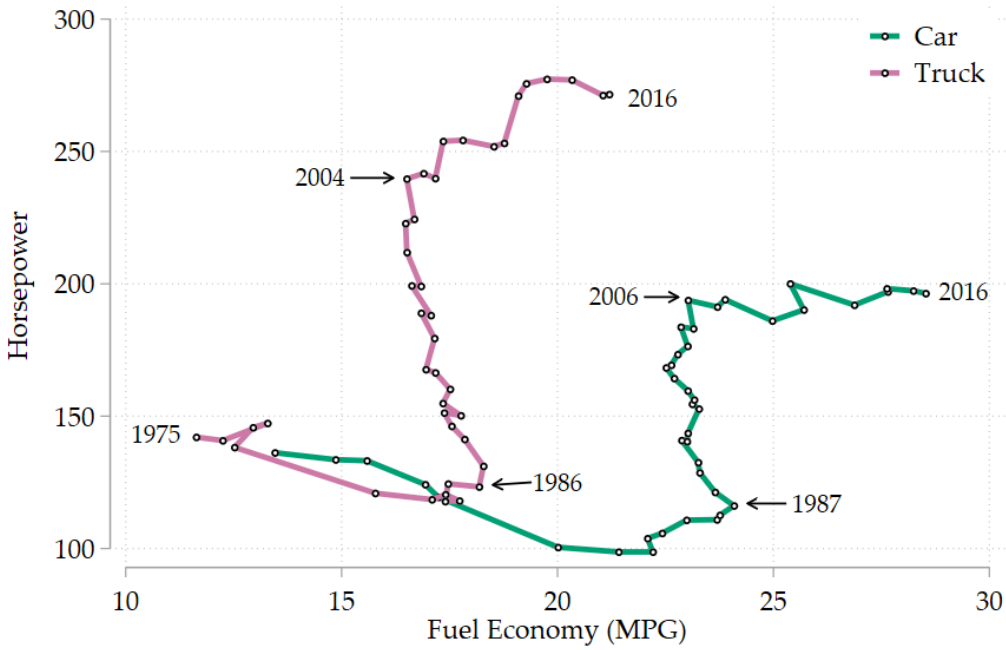
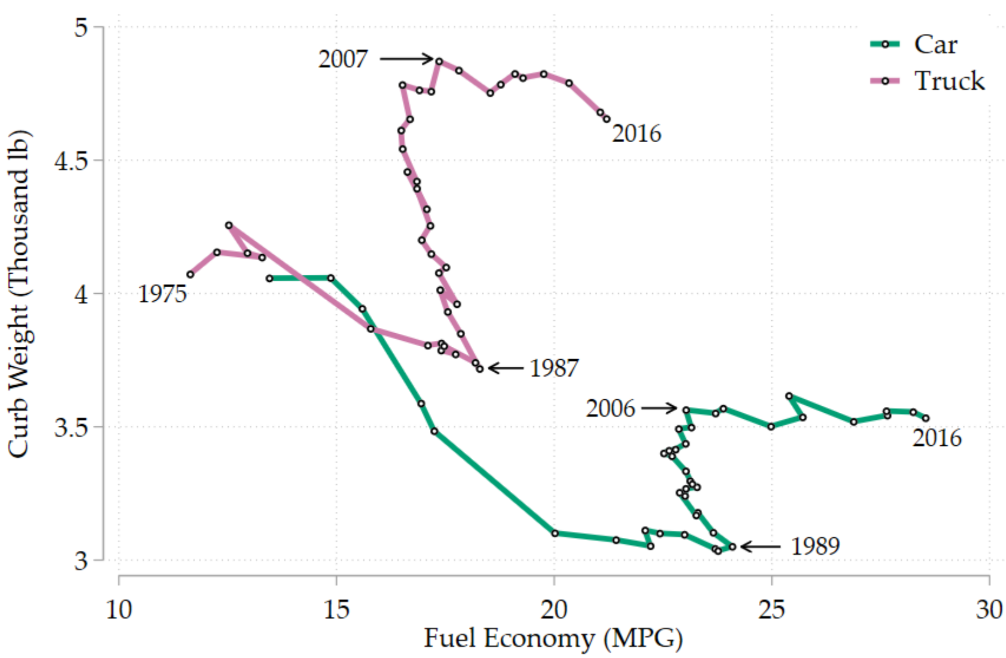


Figure A.2: Trade-off between Fuel Economy and Horsepower and Curb Weight

(a) Horsepower and Fuel Economy



(b) Curb Weight and Fuel Economy



(Notes)