Fuel Efficiency Gains at the Cost of Driving Quality? Implications for Rebound Effects under Uniform and Footprint-Based CAFE Standards*

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Abstract

The estimation of the rebound effect due to improvements in fuel economy under Corporate Average Fuel Economy (CAFE) standards has drawn significant attention in the literature but typically disregarded the potential adverse effect these standards have on the quality of driving experience, which can offset the fuel-economy rebound effect. This paper contrasts the effects of uniform and footprint-based CAFE standards on fuel-economy rebound effects while considering the trade-offs these standards pose between fuel efficiency and driving quality, such as reduced acceleration and vehicle size. Our novel empirical approach leverages vehicle redesign cycles to estimate rebound effects across generations of the same vehicle models, effectively mitigating omitted variable bias and enabling comparisons between the two CAFE regimes. Using data from the 2017 National Household Travel Survey (NHTS) covering approximately 110,000 vehicles in the U.S., we decompose the rebound effect into "fuel-economy" and "driving-quality" components. We conclude that the commonly cited 10% rebound effect in regulatory cost-benefit analyses is overstated—by 10 %-points under uniform standards and 3 %-points under footprint-based standards. This overestimation of fuel-economy rebound effects suggests that regulatory cost-benefit analyses tend to understate the net benefits of CAFE standards by underestimating fuel savings and overstating congestion and accident-related externalities. The trade-off between fuel economy and driving quality was more pronounced in light trucks, indicating that the leniency in truck standards impedes efforts to reduce fuel consumption and tailpipe emissions. These findings have implications for the design of CAFE standards to better align with fuel efficiency and emissions goals.

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1 Introduction

Aiming to curb greenhouse gas and other pollutant emissions, the US government has administered energy-efficiency standards for a variety of household appliances and automobiles over the past decades. Energy economists, however, have found that such standards entail a type of behavioral adjustment known as "rebound effects," suggesting that *ex-ante* engineering estimates of energy savings are unlikely to 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 nearly doubled the industry-wide average fuel economy since its enactment in 1975 through 2018 (US EPA, 2019). In the cost-benefit analysis of the standard, the U.S. Environmental Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) historically employed a 10% rebound effect. In 2018, the NHTSA of the 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 the proposed rollback. 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 that suggest smaller rebound effects (Bento et al., 2018).

In the economics literature, rebound effects of the CAFE standard have been 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 microdata such as odometer readings of individual vehicles in some 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%

[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 the 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 a more comprehensive explanation.

[2] Another focus has been on 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 is 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 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, particularly those that affect the overall driving experience such as acceleration and vehicle size (henceforth "driving quality"). Anderson and Sallee (2016) and West et al. (2017) analytically show that rebound estimates that hold such driving quality constant (henceforth "quality unadjusted") can overestimate (underestimate) the rebound effects of fuel economy standards when driving quality is degraded (improved) for compliance.[4] Gillingham (2020) also emphasizes that conflating fuel-efficiency improvements that materialize exogenously[5] and those that forgo driving quality results in incorrect evaluations of rebound effects. Examining the effect of this trade-off between fuel economy and driving 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 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 effects 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 driving-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 driving quality between

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 the 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.

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 elasticities with respect to fuel economy in the literature do not seem to measure the effect of the CAFE standard precisely. This mismatch occurs primarily because econometric models have failed to capture the business practice in the automobile industry that driving quality is altered at the timing of redesign, which usually occurs every four to six years and at different timings for different vehicle models (Klier and Linn, 2016). For example, the vehicle lineup offered in 2014 includes both vehicle models that continued since before 2012 without reference to the footprint-based standard and those newly redesigned after 2012, whose driving quality is optimized for the new standard. To the extent that the two regimes of the CAFE standard affect the optimal set of driving quality differently, driving behavior would also be affected differently between households owning continued and redesigned vehicles.[7] Therefore, estimating 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 driving quality. 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 redesign 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 driving-quality changes, both of which occur when fuel economy is improved by vehicle redesign. 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 driving-quality, and examine whether the relationship differs before

[7] Unlike gasoline taxes, the CAFE standard does not directly affect households' driving behavior instantaneously. 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.

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 quality adjustment that occurs with vehicle redesign was as much as 9.2% and completely offset the fuel-economy 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 of 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-economy rebound effect after 2012. For cars, the quality adjustment effect still offset the fuel-economy 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 driving 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 **??** provides a theoretical framework to explain how changes in fuel economy will shift the VMT demand curve by the trade-off with driving quality. Section 3 describes our data set, provides observations about the

historical development of driving quality, develops our empirical model, and details how we identify the changes in VMT that are associated with changes in vehicle driving quality. Section 4 reports and interprets the estimation results. Additional tables and figures are presented in the appendices.

2 Decomposition of fuel-economy elasticity of VMT

West et al. (2017) show that VMT elasticity estimates obtained by holding driving quality constant will be biased when changes in fuel economy accompany systematic changes in driving quality. 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 $C(PGAS_i, MPG_j) = \frac{PGAS_i}{MPG_j}$, driving quality ($X_j$), 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 driving quality that are technologically induced by fuel economy improvements. This product term is most likely negative because fuel economy and driving quality, such as acceleration and size, are negatively correlated, whereas such driving quality is typically positively correlated with VMT. Therefore, to the extent that the negative correlation between fuel economy and driving quality is salient, the quality-adjustment term offsets the *ceteris-paribus* rebound effect. If we assume away the correlation between fuel economy and driving quality, 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 driving quality. 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 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 makes driving less fun. 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 driving-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 driving quality 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 driving quality that consumers value, the VMT curve shifts outward and we underestimate the true rebound effects.

Thus, whether and how to control for driving quality 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 of fuel economy standards.

3 Empirical strategy

Our empirical approach introduces a novel framework that uses vehicle redesigns as a key source of variation to achieve identification. Specifically, our method addresses two major challenges prevalent in the literature: isolating the effect of fuel economy improvements from simultaneous changes in driving quality, and accounting for how these changes evolve in response to policy shifts. By focusing on vehicle redesign events, we can capture significant and discrete changes in vehicle characteristics, which are often closely linked to manufacturers' responses to fuel economy standards. This focus enables us to disentangle the intricate relationships between fuel economy, driving quality, and driving behavior, resulting in a more precise estimate of the medium-run rebound effect.

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 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 the 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.[8] Instead, we use quarterly gasoline prices obtained from the Cost of Living Index (COLI) by the Council for Community and Economic Research[9] 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

[8]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.

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

level and compute the quarterly average gasoline prices in each PADD. We also compute the average quarterly gasoline prices for each CBSA. Then, we compute deviations between the COLI-based and EIA-based gasoline prices and impute the quarterly gasoline prices for the anonymized regions.[10] 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 Vehicle redesign helps identify the policy-relevant rebound effects

Our empirical strategy leverages vehicle redesigns as a key source of variation to identify the quality adjustment effect in estimating the fuel-economy rebound effect. Vehicle redesigns, which typically occur every four to six years, introduce substantial changes in driving quality as manufacturers refresh their products. Regulatory changes, such as the CAFE revisions, influence how manufacturers balance improving fuel economy with maintaining driving quality, such as acceleration. This makes redesign events critical for capturing the shifts in driving quality that reflect manufacturers' compliance strategies and market responses.

The historical relationship between fuel economy and acceleration (measured by horsepower-to-weight ratio), as depicted in Figure 2, illustrates how the auto industry has responded to regulatory changes over time by adjusting the balance. Between 1975 and the mid-1980s, manufacturers focused on fuel economy improvements, while acceleration remained relatively static. From the mid-1980s to the mid-2000s, manufacturers shifted their focus to improving acceleration, with stagnating fuel economy. After the mid-2000s, particularly following the 2012 CAFE revisions, manufacturers began to achieve simultaneous improvements in both fuel economy and acceleration, especially for trucks. These industry-wide trends, however, obscure the model-level variation, where significant changes in driving quality often coincide with redesign events. Figure 3 provides a clearer view of these redesign-driven changes. It shows that substantial shifts in driving quality, such as fuel economy and horsepower, are concentrated around redesign events, while continued models barely exhibit changes. This pattern highlights the central role that redesigns play in introducing key adjustments to driving quality.

[10] 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) use confidential NHTS data and identify the household location at the zip code level, which is not applicable to our analysis.

To further examine how manufacturers responded to fuel-efficiency standards, we present in Figure 4 an event-study analysis of redesign-related changes in fuel economy and horsepower-to-weight ratios. A critical observation is the shift in acceleration, as measured by the horsepower-to-weight ratio, particularly after 2011. Trucks, in particular, showed a marked increase in the horsepower-to-weight ratio after 2011 at vehicle redesign, while fuel economy improvements remained relatively stable. This contrast between fuel economy and horsepower-to-weight ratio before and after 2011 suggests that manufacturers adjusted their strategies in response to the stricter standards introduced by the 2012 CAFE revisions by enhancing acceleration without compromising fuel efficiency, especially for trucks.

This observation motivates our empirical strategy, which accounts for vehicle redesign cycles when estimating the fuel-economy rebound effect. Redesigns reveal the broader quality adjustments made by automakers under different regulatory regimes. Such adjustments lead to differentiated compliance strategies for key attributes like fuel economy and driving quality. For instance, the 2012 CAFE revisions aimed to discourage downsizing as a compliance strategy, encouraging manufacturers to maintain vehicle driving quality while improving fuel efficiency.

In the following section, we detail our empirical strategy, which leverages these insights to estimate the fuel-economy rebound effect while accounting for the interplay between fuel efficiency, driving quality, and regulatory environments.

3.3 The empirical model

3.3.1 First step: Estimating VMT demand curve

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 driving 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 be 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-economy VMT

elasticity holding driving quality constant, which precludes the effect of vehicle driving-quality 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 driving quality as the year or year by vehicle model dummy variables. We isolate the portion of VMT that is attributable to driving quality 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.[11] $VMT_{idq,jt}$ is the self-reported annual VMT of vehicle j produced in year t that household i owns (in survey quarter q)[12] 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 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

[11] 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 a comma in equation (5).

[12] 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.

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-economy VMT elasticity and the VMT change caused by vehicle driving-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 driving-quality index measured as the (natural log of) VMT. Since $\xi_{j,t}$ absorbs all the vehicle driving quality, β_1 identifies the average VMT elasticity with respect to fuel cost that is independent of driving quality of any vehicle model and model year. We estimated the effect of changes in vehicle driving 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, and the number of children under the age of 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, and the 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.[13] 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,[14] 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 driving quality that consumers value in their decision on driving mileage. This is consistent with our finding in Section 3.2 that major drivint quality varies almost exclusively at the timing of vehicle redesign. Third, gasoline prices are exogenous to the individual VMT decision. This assumption is commonly

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

[14] 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.

supported in the relevant literature that uses microdata (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.

3.3.2 Second step: Estimating shift of VMT by vehicle driving-quality adjustment

In the second step, we investigate how much of the estimated quality-index VMT is attributable to the bundle changes in driving quality 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 redesigned. It shows the average changes in bundle quality of vehicles at the timing of redesign. 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 redesign 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 driving quality 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,[15] and torque, and each variable is also interacted with $AFTER_t$.[16] It is widely known that these driving qualities 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 driving quality is updated when vehicles are redesigned,[17] 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 redesigned. Accordingly, δ_1 and δ_2 in specification (6) are interpreted as the VMT elasticity with respect to fuel economy when horsepower, curb weight, and torque are forgone. 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 redesign 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 quality adjustments. This gap appears through the difference in how we control for driving quality in our econometric model. The elasticity of VMT that accounts for the quality trade-off is identified by all $\widehat{\delta}$s in Equation (6): $\widehat{\delta}_1 + 100 \times \widehat{\delta}_3$ before 2011 and $\widehat{\delta}_1 + \widehat{\delta}_2 + 100 \times (\widehat{\delta}_3 + \widehat{\delta}_4)$ after 2012. This summation is valid because almost all vehicle attributes, including fuel economy and other unobserved vehicle quality, are to change at redesign. The quality-unadjusted elasticity of VMT is identified only by the coefficients on $\log(MPG)$ in Equation (7): $\widehat{\widetilde{\delta}}_1$ before 2011 and $\widehat{\widetilde{\delta}}_1 + \widehat{\widetilde{\delta}}_2$ after 2012. Since $\widehat{\delta}$s and $\widehat{\widetilde{\delta}}$s are the percentage change in the "shift" of VMT with respect to a

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

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

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

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-economy rebound effect $\widehat{\beta}^*$, the total fuel-economy elasticity of the VMT shift before 2011 is defined as follows:

$$\begin{cases} \widehat{\widetilde{\eta}}_{\text{before}} &= \widehat{\beta}^* + \overline{\Delta VMT}_{\%,\xi,\text{before}} \times \widehat{\widetilde{\delta}}_1 \\ \widehat{\eta}_{\text{before}} &= \widehat{\beta}^* + \overline{\Delta VMT}_{\%,\xi,\text{before}} \times (\widehat{\delta}_1 + 100 \times \widehat{\delta}_3) \end{cases}, \tag{8}$$

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

$$\begin{cases} \widehat{\widetilde{\eta}}_{\text{after}} &= \widehat{\beta}^* + \overline{\Delta VMT}_{\%,\xi,\text{after}} \times (\widehat{\widetilde{\delta}}_1 + \widehat{\widetilde{\delta}}_2) \\ \widehat{\eta}_{\text{after}} &= \widehat{\beta}^* + \overline{\Delta VMT}_{\%,\xi,\text{after}} \times \left\{\widehat{\delta}_1 + \widehat{\delta}_2 + 100 \times (\widehat{\delta}_3 + \widehat{\delta}_4)\right\} \end{cases}. \tag{9}$$

4 Results

4.1 Fuel-economy 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 portfolios. 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 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 an 8.9% fuel-economy 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 readings.

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 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 driving-quality adjustment

Observations in Section 3.2 and empirical evidence in the previous subsection jointly suggest that the VMT demand curve has gradually shifted outward since around the mid-2000s. 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 technological progress without adjusting such driving quality.

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 redesign 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 redesign 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 positive after 2012. Redesign 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 been incurred when driving quality was adjusted.

4.3 Medium-run total 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 redesign, 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-economy 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 driving 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-economy 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. Notably, 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-economy rebound effects in Texas in 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 redesigning vehicles.

5 Conclusion

The size of the rebound effect is one of the key elements in evaluating the effectiveness and costs and benefits of energy-efficiency standards. Even with an extensive list of 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 the U.S. population. We identify the two rebound effects by taking a two-step approach and utilizing vehicle redesign 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 quality adjustment that occurs with vehicle redesign was as much as 9.2% and completely offset the fuel-economy rebound effect between 2005 and 2011, which corrobo-

rates 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 of 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, which most economists have agreed on, still appears to be slightly overstating the fuel-economy rebound effect under the footprint-based CAFE standard. Second, the footprint-based standard for trucks is 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.

Tables

Table 1: Summary statistics

	Mean	SD	Min	Max
Annual VMT (miles/year)	11,124.91	12,413.55	1	200,000
Fuel Cost ($/gallon equivalent)	2.41	0.30	2.13	9.86
Fuel Economy (miles/gallon)	31.94	10.60	8.56	176.92
Per-mile Cost ($/mile)	0.155	0.031	0.020	0.476
Avg. Per-mile Cost of Other Vehicles ($/mile)	0.120	0.030	0	0.431
Number of Household Members	2.44	1.22	1	13
Number of Drivers per Household	1.98	0.77	0	9
Number of Light-duty Vehicles per Household	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-economy Elasticity	0.201	0.105	0.098	0.089
Survey Quarter FE	Y	Y	Y	Y
Model × 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 × Vehicle Class × 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. The 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 redesign (2nd Step)

	(I) Driving quality adjusted ($\widehat{\delta}$)			(II) Driving quality not adjusted ($\widehat{\widetilde{\delta}}$)		
	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
Driving quality (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: Driving quality-adjusted fuel-economy rebound effects

	Period	Fuel economy rebound effect (a)	(I) Quality adjusted		(II) Not quality adjusted		Difference
			Quality effect (b)	Total effect $(c) = (a) + (b)$	Quality effect (d)	Total effect $(e) = (a) + (d)$	$(f) = (e) - (c)$
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) This table shows the decomposition of the VMT elasticity that is associated with fuel economy and other vehicle quality for passenger cars and light trucks between 2005 and 2011 and between 2012 and 2016. "Fuel-economy rebound effect" is the fuel-economy rebound effect estimated in specification (4) in Table 2. Panel (I) shows the VMT elasticity with respect to fuel economy with forgone horsepower, curb weight, and torque, as defined in equation (8). Panel (II) shows the VMT elasticity with respect to fuel economy holding horsepower, curb weight, and torque constant, as defined in equation (9).

Figures

Figure 1: Decomposing the change in VMT from increased fuel economy

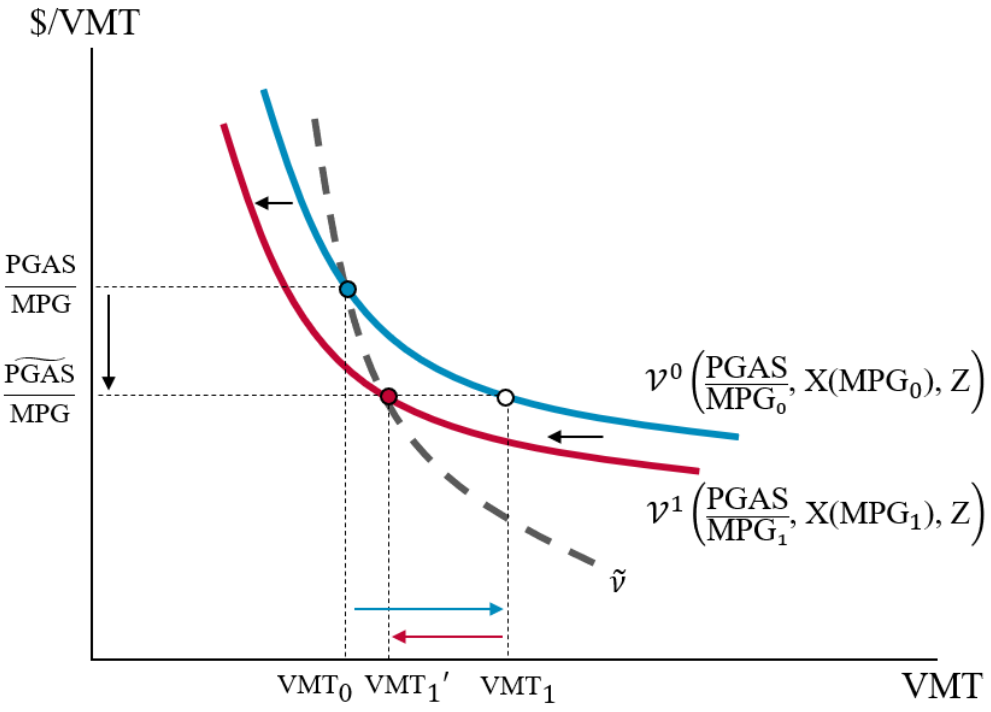
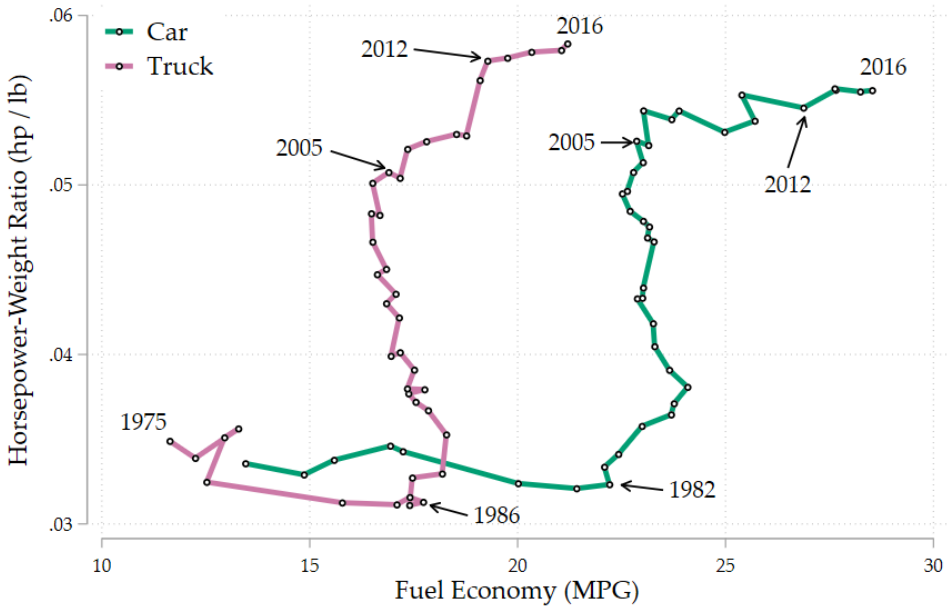


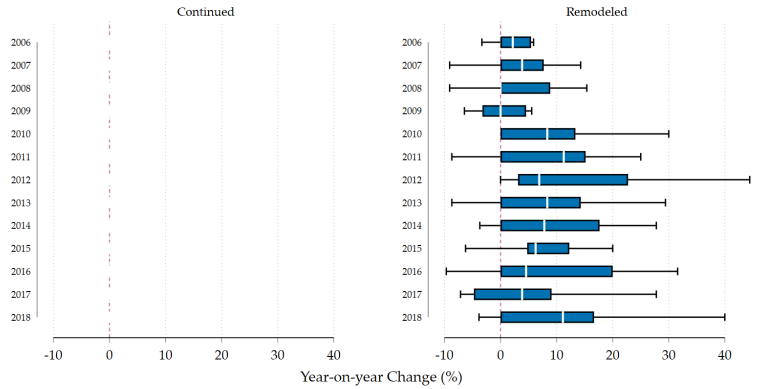
Figure 2: Trade-off between fuel economy and acceleration



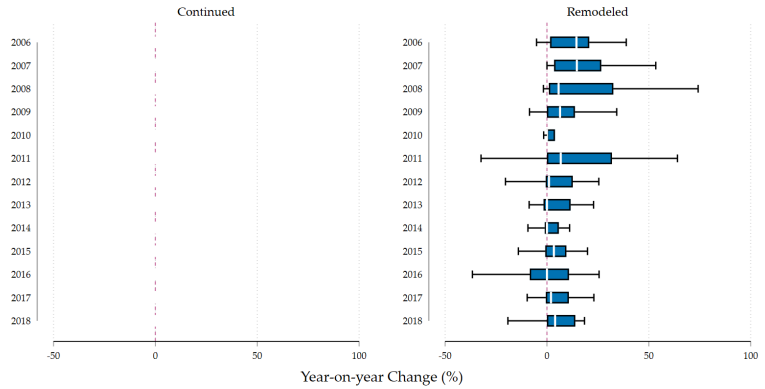
(Notes) This figure plots and connects the pairs of average fuel economy and average acceleration (measured as the ratio of horsepower to curb weight) for Cars and Light trucks between 1975 and 2016. Horizontal (vertical) movements indicate an improvement in fuel economy (acceleration).

Figure 3: % Year-on-year change in driving quality for continued and redesigned vehicles

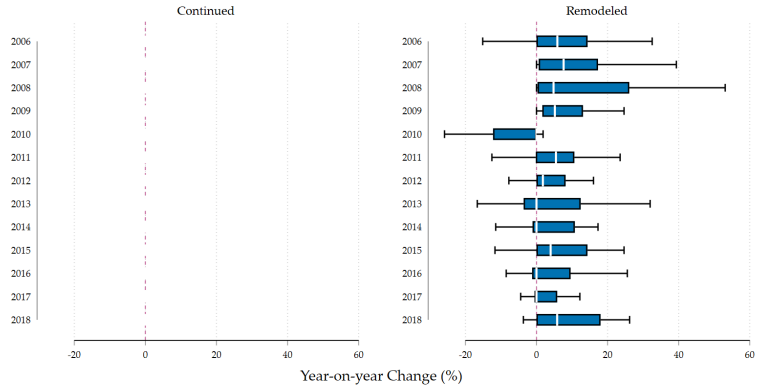
(a) Fuel economy



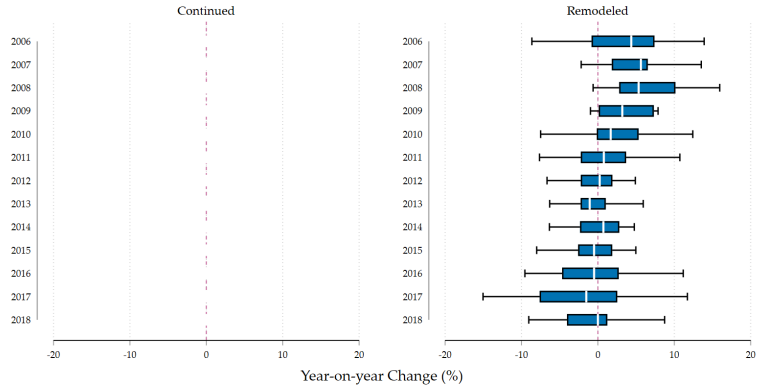
(b) Horsepower



(c) Torque



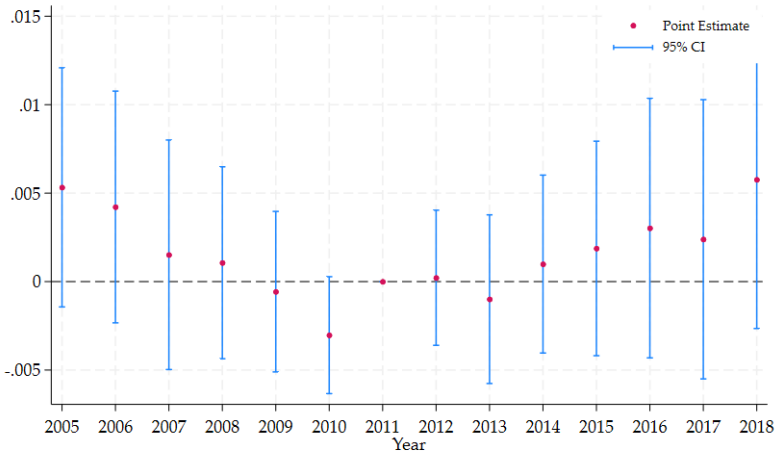
(d) Curb weight



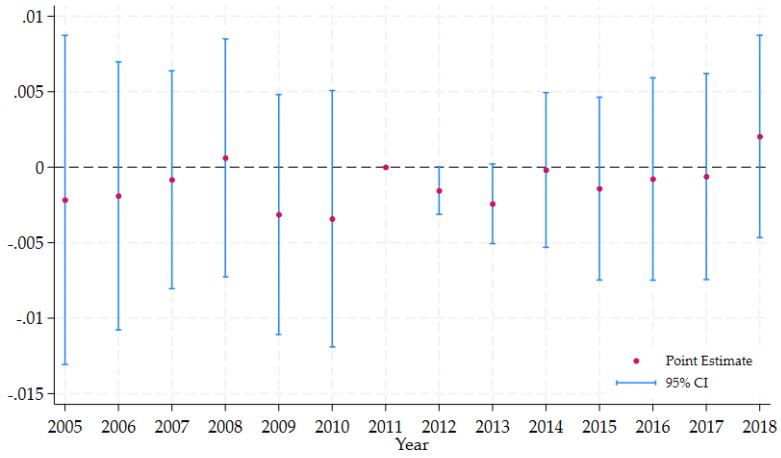
(Notes) Each figure shows the box plot of year-on-year % changes in each of the driving qualities for vehicle models that were continued from previous years and those that were newly redesigned.

Figure 4: Changes in fuel economy and horsepower-to-weight ratio at vehicle redesigns relative to 2011

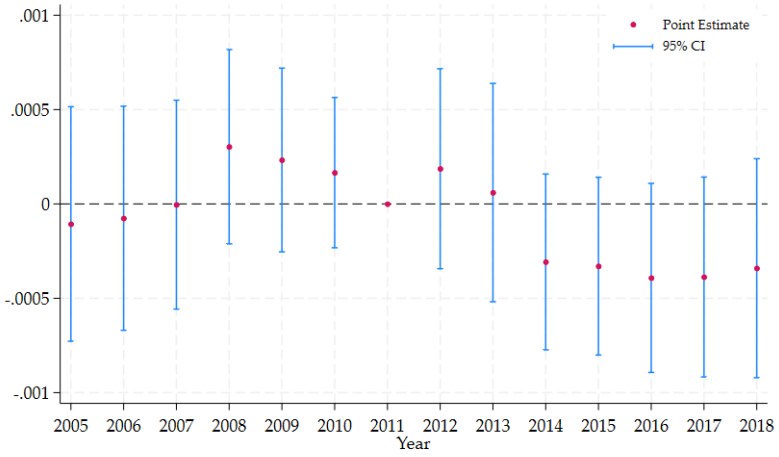
(a) Fuel economy (Cars)



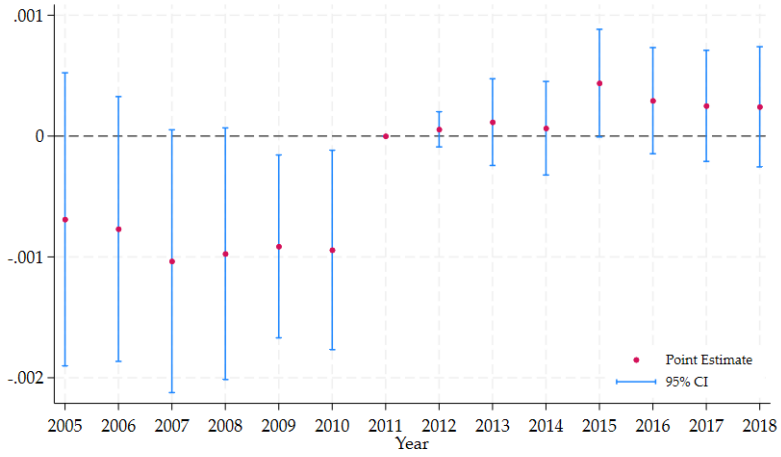
(b) Fuel economy (Trucks)



(c) Horsepower-to-weight ratio (Cars)



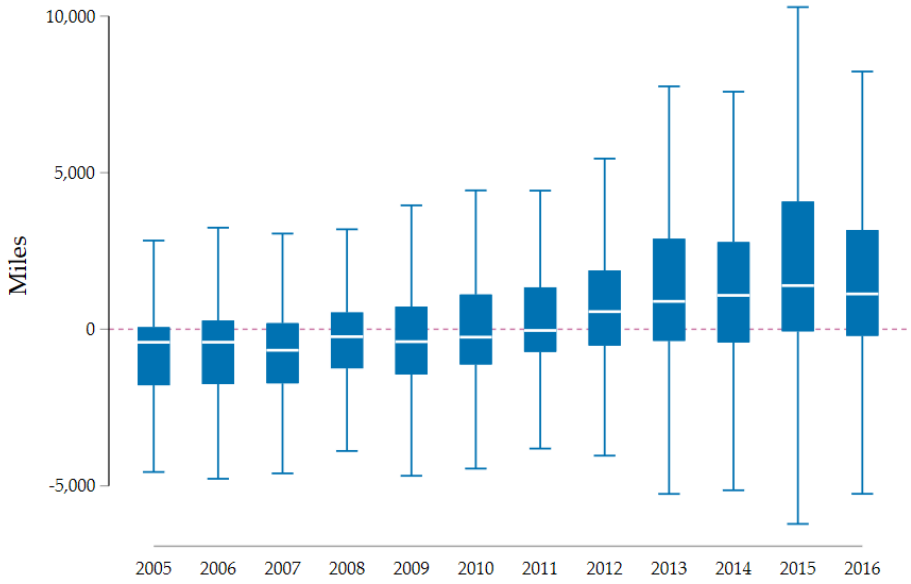
(d) Horsepower-to-weight ratio (Trucks)



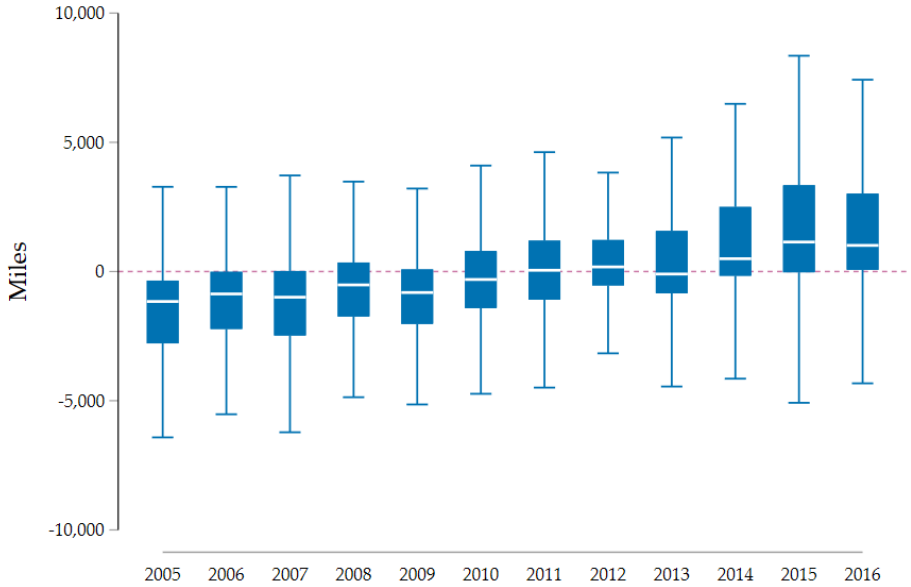
(Notes) The figures show changes in fuel economy (MPG) and horsepower-to-weight ratio at vehicle redesigns relative to the year 2011, serving as the baseline. Confidence intervals at the 95% level are shown for each year.

Figure 5: Yearly distribution of vehicle quality index in VMT

(a) Passenger cars



(b) Light trucks



(Notes) The box plot shows the distribution of the VMT each year. The VMT is estimated by $\hat{\xi}_{jt}$ in Equation (5) and thus indicates the portion of VMT associated with the overall vehicle quality of each vehicle model by model year. The VMT is shown as the deviation from the overall mean.

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Appendix A Appendix

Figure A.1: Historical development of the CAFE standard

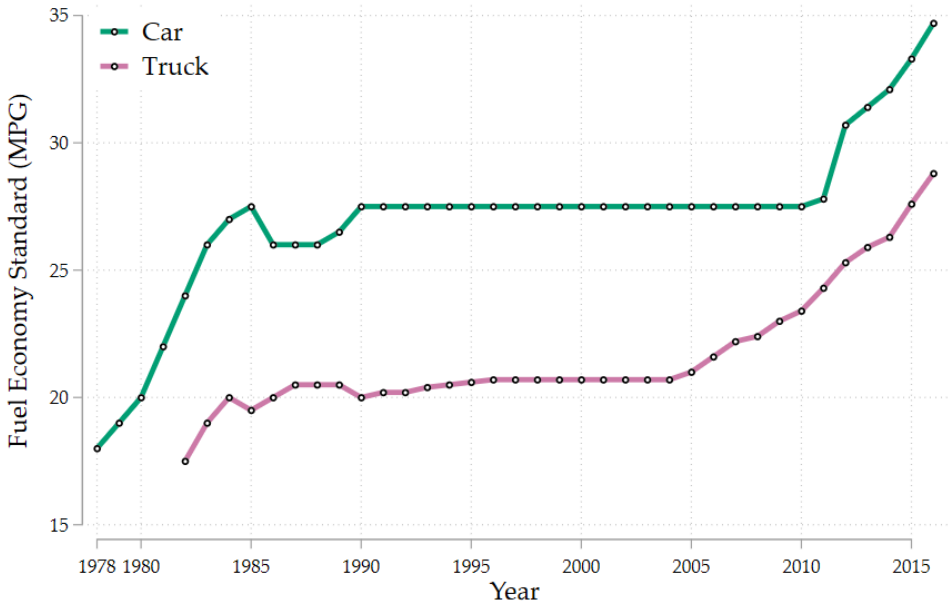
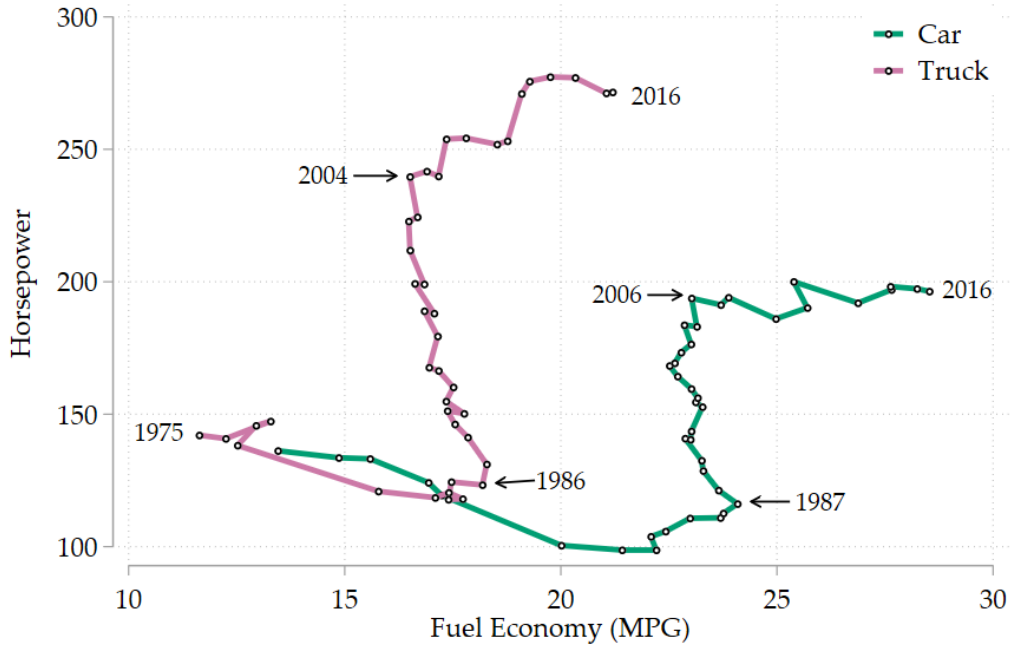
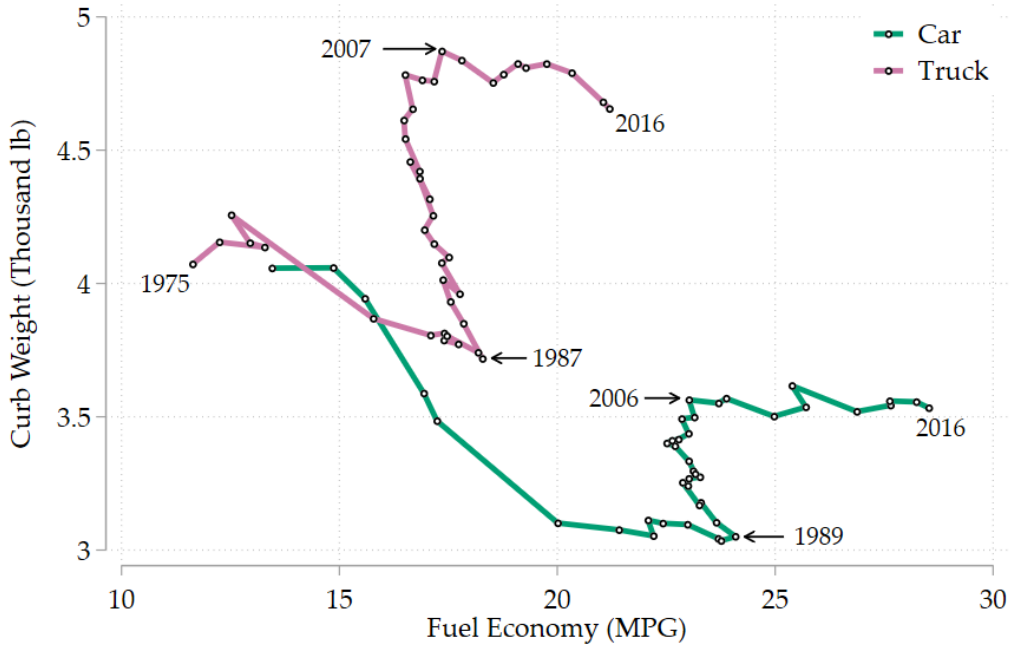


Figure A.2: Trade-off between fuel economy, horsepower, and curb weight

(a) Horsepower and Fuel Economy



(b) Curb Weight and Fuel Economy



(Notes) These figures plot and connect the pairs of average fuel economy and horsepower (A.2a) average fuel economy and curb weight (A.2b) for Cars and Light trucks between 1975 and 2016. Horizontal movements indicate an improvement in fuel economy and vertical movements indicate an increase in horsepower and curb weight.