US gasoline response to vehicle fuel efficiency: A contribution to the direct rebound effect

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Abstract

This study measures the response of gasoline consumption to improved vehicle fuel efficiency (miles per gallon). Although an inverse relationship exists, the percentage decline is always less than the percentage efficiency improvement. As usually measured by past researchers, the long-run response in this study is approximately 80% of the efficiency improvement. The remaining 20% is the direct rebound effect and comports well with previous estimates. However, this rebound estimate escalates to 40-50% if horsepower or vehicle size are controlled. Even larger estimates (about 70%) are possible if carmakers change both fuel efficiency and horsepower when required to meet energy efficiency standards. Larger rebound effects are also possible when VFE improvements also reduce gasoline prices, but these price reductions may also improve welfare.

JEL classification: Q41; Q48; O33

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1. Introduction

Despite rapid vehicle energy-efficiency improvements, the transportation sector has contributed substantially to the growth in total end-use energy consumption in a number of richer economies since the oil-embargo years. In the United States and prior to the 2020 COVID pandemic, end-use energy consumption grew 48.1% above 1972 levels within transportation, while it increased 12.7% outside of the transportation sector (US Energy Information Administration, 2023). This experience reflects a plethora of economic and social factors such as the diversity of end-use service growth in the various sectors, but it is still intriguing to wonder why demand has remained so strong in a sector experiencing significant improvements in energy efficiency.

This above inquiry is closely associated with what has been termed the direct energy rebound effect. Policymakers are strongly interested in this effect because it influences how effective are policy mandates to improve energy efficiency in terms of miles per gallon in the vehicle stock. When vehicle fuel efficiency (VFE) improves for automobiles, fewer gallons are required to drive each mile. However, there may also be a "snapback" effect where some lost energy use is returned to the economy because consumers drive more miles in response to lower costs per mile that result from fewer gallons per mile. In the absence of major changes in lifestyles, this response is likely to be small because gasoline is a relatively minor cost in operating a vehicle relative to insurance, depreciation, vehicle registration and other non-fuel costs. Moreover, additional travel may be restricted by time costs that can be substantially greater than the reduced fuel costs attributable to greater efficiency (Small and Van Dender, 2007.; Schafer and Victor, 2000; Brencic and Young, 2009). In the longer run, however, residents may commute longer distances for work to take advantage of lower-cost housing located further distances from major employment centers.

The energy rebound effect is defined as the ratio of the snapback effect relative to the initial energy-efficient improvement for the relevant energy-using capital stock. If the rebound effect remains below 100%, energy use declines but by less than what would be expected from the initial energy-efficient improvement. If the rebound effect exceeds 100%, “backfire” exists because energy use will actually increase. As discussed in the next major section, this direct rebound effect may also be accompanied by other indirect rebound effects that operate in other sectors of the economy.

The snapback response is very difficult to measure explicitly because the appropriate time-series data on equipment energy efficiency are challenging to obtain. As a result, direct rebound effects are usually measured by assuming that the price elasticity of gasoline demand is a reliable proxy for the direct rebound effect. Without explicit testing of this assumption, however, it is difficult to evaluate if this proxy is appropriate and unbiased. This analysis explores this empirical issue explicitly through the use of a time series on vehicle fuel efficiency (VFE).

The arguments for relatively low direct rebound effects seem reasonable as long as the new capital-stock vintages are changing only the energy efficiency of the automobile and none of its other attributes. In practice, however, policy mandates have improved heat-content efficiency without restricting automobile producers from changing other attributes valued by vehicle owners. Producers of energy-using capital stock will redesign their product to align them with consumer preferences when confronted with government mandates that force improved BTU efficiency. Knittel (2011) documents that automobile producers responded to the US corporate average fuel efficiency standards by improving a number of other attributes like horsepower, weight, size and similar attributes that may improve the overall travel experience of many US drivers. These additional attributes may stimulate additional driving by vehicle owners that will increase the amount of the snapback above and beyond the standard direct rebound effect often discussed in the literature. This response might be called a *multi-attribute effect* because constraints on energy efficiency alone will not prevent automobile producers from substituting other attributes that could potentially offset some of the energy efficiency initially intended by policymakers. For this reason, it is important to evaluate this issue empirically if one wants a more robust perspective on how policy changes and market behavior interact.

This research provides empirical evidence that allows for a wider perspective on how VFE shapes the demand for gasoline. The analysis shows that explicit measurement of VFE provides a better indicator of gasoline use trends than other approaches sometimes used in the literature. The specifications behind these estimates do not constrain the direct rebound effects to be the same as the price elasticity. Initial tests of the direct rebound effect based upon these equations provide direct rebound effects that are generally small under certain conditions. These estimates are generally higher than those based upon the price elasticity from the same regression, but they appear broadly consistent with the previous literature. However, it is argued that these estimates are of more limited value for policymakers who want to know the amount of realized energy savings from energy-efficiency mandates.

Section 2 below reviews various strands of the economic literature that relate directly to this inquiry. It discusses methodologies for incorporating technical change in gasoline studies, the range of price elasticities existing in the literature, and general principles relating to the rebound effect. The data sources and properties together with the empirical approach are discussed in section 3. Key results are presented and discussed in section 4 for a range of specifications that demonstrate the role of VFE. Additional results that highlight the influence of other vehicle attributes are highlighted in section 5. Simulations based upon the regression analyses are presented in section 6 to explore the direct rebound effect when other attributes are changing and when gasoline prices respond. Readers with less interest in the econometric approach should find this section useful for illustrating the important findings in this study. Summary results and concluding remarks are contained in the final section.

2. Literature Review

This section highlights a few key topics that relate to this analysis's main contribution. These issues are the problems created by estimating the effects of technological progress on energy use, a very brief summary of the principal findings on the price and income elasticities of the vast literature on this topic, and a few important but related strands from an extensive set of studies on the energy rebound effect.

2.1. Technological Progress

Technological advancement in the efficiency of the capital stock plays an important role in shaping the derived demand for energy (Fisher and Kaysen, 1962). Usually, the unavailability of reliable data makes it difficult to incorporate this concept adequately in empirical studies. As a result, researchers (e.g., Beenstock and Willcocks, 1981) often include a simple deterministic trend as one way to represent the exogenous effect of more efficient capital. This approach is crude but may be preferable to ignoring the concept altogether (Beenstock and Willcocks, 1983). It may be sufficient when technological improvement moves steadily over time, but often this process is motivated by general economic conditions and external policy mandates.

In the absence of appropriate technical measures of the capital stock's energy efficiency, another approach would be to allow the symmetric price elasticity to incorporate some of the effect of technological progress (Kouris, 1983). Dargay and Gately (1997) and Gately and Huntington (2002) found this approach unsatisfactory because different price experiences caused dissimilar responses. They argued that the capital-stock turnover and adoption of more efficient equipment would require one to incorporate the direction of energy price changes as well as their relationship to previous energy prices. Based upon earlier economic contributions on agricultural supply by Wolffram (1971) and Traill et al. (1978), a number of studies (Dargay and Gately, 1997, Haas and Schipper, 1998, Gately and Huntington, 2002) replaced the concept of a symmetric price response with an asymmetric price response (APR). One conclusion held that there is imperfect price reversibility where price increases influenced energy demand more than price decreases. A more dramatic effect was observed for what these authors termed maximum or peak price effects, which essentially were energy price levels leading up to the late 1970s and early 1980s that were substantially and significantly larger than prior price levels. Hughes et al (2008) and Ryan and Plourde (2002) also found larger impacts during the 1970s. A principal reason for this larger impact was the different response in capital turnover and adoption of new equipment (e.g., see Gately and Huntington, 2002). In fact, one of the major errors in oil price projections during the 1980s has been attributed to the smaller expansion in oil demand as oil prices declined than would have been expected from price elasticities estimated for the 1970s (Huntington, 1994).

Hunt et al. (2003a, 2003b) developed another useful technique by replacing the deterministic trend with an underlying energy demand trend (UEDT) derived stochastically from an unobserved components model (UCM). Their broader UEDT measure incorporated not only improved capital stock efficiency but also shifts in regulations, economic and demographic structure, and consumer preferences. In later studies, Adeyemi et al. (2010) and Adeyemi and Hunt (2014) successfully demonstrated that a richer explanation flowed from a combination of the asymmetric price responses (APR) and the UEDT approaches. Rodrigues et al (2018) and Dilaver and Hunt (2021) have applied this combined approach to evaluate gasoline demand in Brazil and the USA, respectively. There exists a sharp break in the stochastic unobserved trend in 1979 in the US gasoline study.

The current analysis departs from these approaches in order to focus specifically on the turnover of capital on the technical efficiency of automobiles. As stated above, the UEDT technique is too broad and may encapsulate many other factors besides energy efficiency. For similar reasons, it is shown in the next section that there is no convincing evidence that vehicle efficiency can be related to the upward and downward shifts in gasoline prices alone. A key advantage of the current approach, however, is that the estimates allow us to evaluate the effects of vehicle fuel efficiency on US gasoline consumption. To what extent do more efficient vehicles decrease gasoline use rather than stimulate additional usage through the energy rebound effect?

2.2. Price and Income Responses

There have been multiple empirical studies that have investigated the role of price and income on gasoline consumption at the country or aggregate level. Depending upon data availability and country, these estimates often include a range of different control variables that may include demographic, socioeconomic and macroeconomic conditions that shape car ownership, number of trips and local and highway mobility (Graham and Glaister 2004). The most striking result in comparing estimates across studies is the extremely wide range that they cover.

In an international panel of for 35 OECD countries covering the 1978-2016 period, Liddle and Huntington (2020) estimated long-run price elasticities of about -0.58 and long-run income elasticities of about 0.58. The inverse responses to price are smaller (less negative) for the developing economies in their study, while the positive responses to income (GDP) were larger. These estimates refer to the mean estimate for all OECD countries rather than for the USA alone. These long-run OECD estimates are slightly below but broadly in the same scale as those found previously in the literature. In comparing their estimate above with previous findings, these same authors reported the average price and income elasticities of gasoline demand from various surveys (Dahl and Sterner 1991; Graham and Glaister 2004; Huntington et al. 2019) and meta-analysis (Brons et al. 2008; Havranek et al. 2012; Havranek and Kokes 2015; Labandeira et al. 2017) of previous empirical studies. Estimates are primarily from the mature OECD nations. The average responses varied substantially across studies. The average short-run price elasticities ranged between -0.09 and -0.36 with a mean of -0.26, while the average short-run income elasticities ranged between 0.10 to 0.64 with a mean of 0.38. The average long-run price elasticities ranged between -0.31 and -0.86 with a mean of -0.69, while the average long-run income elasticities ranged between 0.23 to 1.21 with a mean of 0.79.

The above estimates refer to elasticities for a range of different countries. Although one might expect gasoline consumption to be less responsive to price in the United States due to the much lower population density and absence of alternative commuting options like public transportation, available evidence suggests a considerably wide range. In a study based upon essentially the same US data for consumption, prices and GDP as used in the current study, Dilaver and Hunt (2021) report income elasticities near 0.40 in both the short and long run and long-run price elasticities between -0.14 and -0.31, depending upon various price components (as described below). Their short-run price elasticities ranged between -0.04 and -0.27. Once again, these estimates from a single study fall within a very wide range of elasticities found in other US gasoline studies that the authors review. In US gasoline estimates for both price and income elasticities based upon national data, these authors show price elasticities between -0.03 and -0.40 in the short run and between -0.08 and -1.07 in the long run. They also report income elasticities ranging between 0.06 to 0.33 in the short run and between 0 .69 to 1.03 in the long run. Their own income estimates for both the short and long run fall midway between these two sets of elasticities.

Many countries represent a relatively small share of the integrated world oil market. Under these conditions, it is likely that gasoline prices in these countries are exogenous because domestic demand shifts do not influence world gasoline markets. This situation may not be the case for the United States, where gasoline markets account for a large share of the world oil market. Price responses based upon endogenous rather than exogenous gasoline prices appear larger, but the estimates appear quite sensitive to assumptions about expectations (Davis and Kilian, 2011; Coglianese et al, 2017). For this reason, the current study also explores the effect of considering gasoline prices as an endogenous variable in section 5.

The principal conclusion from reviewing past studies is that price elasticities can range widely depending upon region, time period, and empirical methodology. Price elasticities can be important in shaping the amount of direct rebound, and hence the effects of vehicle fuel efficiency on gasoline consumption. This study explores multiple specifications in an effort to apply a more robust set of tests in evaluating the effects of vehicle fuel efficiency.

2.3. *Energy Rebound Effect*

There exists a number of useful efforts to summarize the literature on the possibilities for an economywide energy rebound resulting from energy-efficiency improvements. Studies frequently differ on what factors are included or excluded in their definition of the rebound effect or how they define energy efficiency (Turner, 2013). Moreover, they often focus on different applications and energy sectors and fuel types that may respond quite differently (Schmitz and Madlener, 2020). These problems often contribute to a very wide range of estimates that can differ not only in magnitude but also direction.

Although it can be and is often interpreted in a number of different ways, the rebound effect generally captures the extent to which actual, observed changes in energy demand react when new energy efficiency technologies are imposed exogenously by policy or surprise developments rather than chosen endogenously by energy consumers. The rebound effect refers to the amount of energy that is pushed back into the economy after energy efficiency has been improved by some given percent. Survey articles generally separate these responses into direct and indirect rebound effects.

Direct rebound effects exist when energy-efficiency improvements reduce the costs of the relevant energy service demand relative to other service demands (Khazzoom 1980). This effect essentially reduces the energy input requirement for each unit of the energy service demand, thereby decreasing its price in energy-efficiency terms. Its magnitude is positive but often considered to be small and well below unity, based upon theory that calibrates it to empirical estimates of the energy price elasticity. This concept measures the substitutability between energy and other inputs for the specific energy service demand.

Gillingham et al (2016) provide a valuable survey of estimates of the direct rebound effect for a range of different applications including road travel. They note several problems in estimating this concept, including the fact that it matters whether the shift towards more energy efficiency is cost-free or costly. Eventually, they adopt the standard assumption that the direct rebound effect can be approximated by the price elasticity of energy for each specific energy-using application. They focus upon short- to mid-term responses to price because long-run estimates depend upon the use of lagged consumption. For gasoline consumption in developed countries, they suggest a range between 5% to 40%, with most clustering in the 5% to 25% interval.[1] In another useful survey of past research, Sorrell et al (2009) confirm the above range, suggesting that the direct effect for transportation probably lies between 10% and 30%. Moshiri and Aliyev (2017) emphasize in their Table 1 the considerable diversity in direct rebound effects for gasoline in past studies, which range from 3% to 30% for studies on the United States. Once again, efficiency is proxied by fuel costs in these estimates. These estimates ignore the effects for other goods and services. When income is not spent on the service demand using the more efficient energy, the released income will be reallocated to other goods and services that may increase or decrease overall energy use. These effects are often small because the released income represents a relatively small share of the total economy.

There will also be general-equilibrium or macroeconomic effects that affect the remaining economy beyond the energy service demand experiencing the technology improvement. Often described as indirect effects, they include the additional snapback in consumption caused by a lower gasoline price (Borenstein, 2015; Gillingham et al., 2016), wage

[1] Surveys reporting estimates that include other sectors as well as road transportation suggest a wider and less precise range. Greening et al (2000) concluded that available estimates of the direct effect at that time suggested a modest rebound effect falling in the 0-50% range. In a later review, Sorrel (2009) argues that the direct rebound effect is unlikely to exceed 30% in the richer OECD nations for many consumer expenditures.

adjustments as more productive energy replaces labor (Lemoine, 2020), shifts in the cost of supplying capital as returns to capital and investment change (Saunders, 1992; Bohringer and Rivers, 2021), and reallocation between economic sectors. Since the energy-producing industry is frequently more energy-intensive than many other sectors, energy efficiency in other sectors may contribute to more rather than less energy reductions (Turner, 2013).

Surveys are more cautious in defining the size of the total rebound effect that also includes the indirect effects. A representative result from different scenarios evaluated by the general equilibrium modeling of Böhringer and Rivers (2021) is 60%, while a review by Stern (2020) highlights several recent estimates suggesting almost 100% total rebound.

The relevant estimates for the analysis described below, however, will be the 5-25% direct rebound effect for gasoline discussed above. Most prior estimates of the direct rebound effect are linked to the price elasticity of gasoline consumption rather than estimated directly from policy-mandated VFE improvements. The potential bias of using these past estimates based upon the price elasticity for gasoline demand is unknown. They may understate the direct rebound effect because gasoline prices fluctuate over a longer term cycle, inducing relatively modest responses. By contrast, vehicle fuel efficiency improvements are more permanent and not as easily reversed ((Moshiri and Aliyev, 2017)). On the other hand, this approach may overstate the direct rebound effect if consumers view gasoline prices to be more visible than vehicle fuel efficiency improvements (Gillingham et al, 2016) or if they respond asymmetrically to gasoline prices with smaller adjustments to price cuts (Sorrell et al, 2009). The current analysis below explores this issue with a more explicit estimate based upon data on VFE trends that may avoid these potential biases.

3. Analytical Approach and Data

3.1 Empirical Specification for Incorporating VFE

The basic conceptual framework begins with a capital-stock utilization approach where per-capita gasoline (*G*, in gallons) equals the ratio between per-capita mobility (*M*, in vehicle miles driven) and the average vehicle fuel efficiency (*J*, in miles per gallon) of the automobile stock. The second term *J* represents the capital stock adjustment, where the vehicle fuel efficiency is the inverse of the vehicle fuel intensity. The first term *M* incorporates any adjustment in the capital stock utilization, where equipment efficiency has already been selected. Controlling for an intercept term (m_0) and other exogenous variables (X_m), per-capita mobility (the utilization variable) declines with higher gasoline prices (*P*, in $ per gallon) and increases with higher average vehicle fuel efficiency (J, in miles per gallon) because the cost per mile is less. Converting all variables to logarithms and expressing them as small letters yield this expression for gasoline consumption and vehicle mobility, respectively:

$$g = m - j$$

$$m = m_0 - \beta p + \phi j + \gamma x_m$$

Energy and environmental policy analysts appear most interested in the effect of technical progress on gasoline consumption (and any associated environmental or societal damages tied directly to gasoline usage) rather than on travel mobility. Solving for g yields a per-capita gasoline consumption equation:

$$g = m_0 - \beta p - (1 - \phi) j + \gamma x_m$$

where x_m includes real per-capita GDP and could also incorporate other possible variables, such as vehicle horsepower, vehicle weight, household size and total vehicle registrations.

Many previous studies on the rebound effect impose the constraint that β≡ - ϕ based upon the conceptual premise that the only influence of more efficient vehicles is that the shift changes the cost per mile. This restriction makes sense only if consumers view permanent cost changes caused by more efficient vehicles are identical to those caused by fluctuating gasoline prices. It also assumes that producers and consumers of the energy-using capital are concerned solely with the BTU efficiency of the equipment. Additionally, If consumers value other attributes like horsepower or interior passenger and cargo space in their driving patterns and producers meet these demands when they are forced by mandates to improve fuel efficiency, the assumption may not be valid. Instead, the approach here will be to allow the data to determine its validity. It should be noted that this assumption adopted by the standard approach tends to tie the rebound effect to the price elasticity of demand, which often tends to be very low in most empirical studies.

The parameter $1 - \phi$ measures the elasticity of gasoline consumption to changes in the vehicle fuel efficiency. The rebound effect will equal ϕ, the difference between the potential impact (=1) and this estimated response to vehicle fuel efficiency $(1 - \phi)$. Vehicle efficiency has no influence on gasoline consumption if ϕ = 1, because the rebound effect completely offsets the potential fuel efficiency improvement. If ϕ = 0, all efficiency improvements materialize as reductions in gasoline consumption and no rebound effect exists. Although unexpected, the rebound effect could be sufficiently large (ϕ > 1) as to produce "backfire" conditions where gasoline consumption expanded with vehicle fuel efficiency.

Moreover, this estimated response to VFE allows one to test whether the direct rebound effect (ϕ) equals the absolute value of the price elasticity of demand (-β). Beginning with this equality, one can subtract the potential effect (=1) from both sides and rearrange terms to derive the following relationship:

$$\beta + (\phi - 1) = -1$$

where the left-hand side represents the sum of the price and VFE elasticities. This relationship will be tested for the long-run responses in the following empirical section.

Households adjust their capital vintages and utilization rates gradually over time. They have some flexibility in substituting new and older vintages. For this reason, a Cobb-Douglas function combining new and past vintages is specified:

$$\bar{g} = (1 - \lambda)g + \lambda L.\overline{g}$$

where $\bar{g}$ is the average per-capita gasoline consumption, g is the new per-capita gasoline consumption, λ represents the weight for old vehicles, and the *L.* operator indicates the first lag. Under these conditions, the dynamic empirical specification becomes:

$$\bar{g} = (1 - \lambda)\,[m_0 - \beta\,p - (1 - \phi)j + \gamma\,x_m] + \lambda L.\overline{g} \tag{1}$$

This functional form will be referenced as the *vfe* specification when x_m includes only real per-capita GDP. Household size and vehicle registrations can be added to the equation to test for robustness.

As a precursor, consider the situation when information about *j* is unavailable. Excluding this variable and replacing x_m by per capita income (*y*) yield an initial benchmark which will be referred to as the *py* specification:

$$\bar{g} = (1 - \lambda)[m_0 - \beta\,p + \gamma\,y] + \lambda L.\bar{g} \tag{2}$$

Average per-capita gasoline consumption is estimated as an ARDL (1 0 1) specification that includes price and per-capita income only, with no explicit representation for any technology factors like the VFE trend. The effects of price are reversible, where the response to price cuts mirrors its counterpart for price recoveries.

3.2 Additional Vehicle Attributes

Vehicle horsepower is an important additional attribute that can be added to the *vfe* specification (1), because consumers have revealed an important preference for more powerful cars with greater acceleration. These additional services could influence mobility. However, there exists considerable correlation between vehicle horsepower and the VFE variable because both trends began rising since the late-1970s. As a result, the VFE variable in the *vfe* specification could be incorporating some of the effect imposed by the missing variable, vehicle horsepower. Adding vehicle horsepower (hp in logarithms) to the *vfe* specification yields the following *vfehp* specification:

$$\bar{g} = (1-\lambda)\,[m_0 - \beta\, p - (1-\phi)\, j + \gamma_y\, y + \gamma_{hp}\, hp] + \lambda L.\overline{g} \tag{3}$$

Vehicle weight (w in logarithms) is another important additional attribute that can be added to the *vfe* specification (1), as consumers have revealed an important preference for larger cars that can provide additional services and influence mobility. Adding this variable to the *vfe* specification yields the following *vfew* specification:

$$\bar{g} = (1-\lambda)\,[m_0 - \beta\, p - (1-\phi)\, j + \gamma_y\, y + \gamma_w\, w] + \lambda L.\overline{g} \tag{4}$$

Note that the collinearity between VFE, horsepower, and weight prevents one from deriving meaningful results from an equation combining all three variables.

All of the above relationships treat vehicle fuel efficiency *(j)* as an exogenous variable that is not influenced by gasoline prices. A more appealing and perhaps robust treatment would be to replace the vehicle fuel efficiency variable with the following relationship:

$$j = j_0 - \alpha p^*$$

where $p*$ will be those components of the gasoline price variable that motivate improved vehicle fuel efficiency. Other exogenous improvements will be incorporated by the j_0 factor that is introduced as an intercept term that may fluctuate with exogenous policy shifts. Both effects are described below under section 4 that discusses results. When this relationship replaces the j variable in equation (1), the reduced-form specification (now referenced as *vfexp*) incorporating the above recursive j effect becomes:

$$\bar{g} = (1 - \lambda) [m_0 - \beta p - (1 - \phi)(j_0 - \alpha p^*) + \gamma x_m] + \lambda L.\overline{g} \tag{5}$$

3.3. Data Sources and Properties

The analysis explores the above specifications for estimating U.S. time series on per-capita gasoline consumption. The full sample covers annual observations over the 1949-2019 period. It excludes the pandemic period beginning in 2020 when the initial COVID outbreak and health moratoriums severely curtailed mobility and created sudden economic dislocations that could not be appropriately incorporated with annual data.

Among the principal variables, per-capita gasoline consumption equals gasoline consumption divided by population. The analysis follows Huntington (2010a) and Dilaver and Hunt (2021) by using thousand barrels per day of U.S. gasoline that are provided by U.S. Energy Information Administration, US product supplied of finished motor gasoline, retrieved from https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=MGFUPUS2&f=A, June 14, 2023. These estimates are expressed on a per-capita basis by dividing by total U.S. population (converted to millions) that are provided by U.S. Census Bureau, Total Population: All Ages including Armed Forces Overseas [POP], retrieved from FRED, Federal Reserve Bank of St.

Louis; https://fred.stlouisfed.org/series/POP, June 14, 2023. The U.S. gasoline price is indexed to 1982=100 and is extracted from U.S. Bureau of Labor Statistics, Producer Price Index by Commodity: Fuels and Related Products and Power: Gasoline [WPU0571], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/WPU0571, June 14, 2023. Real gasoline prices are derived by dividing these estimates by the consumer price index (2012=1.00) using 2012 prices from U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL, June 14, 2023. An additional variable for the maximum gasoline price experienced in each year is based upon this series and is discussed later in the analysis. Per-capita Real GDP in chained 2012 Dollars is extracted from U.S. Bureau of Economic Analysis, Real gross domestic product per capita [A939RX0Q048SBEA], retrieved from FRED, Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/series/A939RX0Q048SBEA, June 14, 2023. Vehicle fuel efficiency is measured as average miles per gallon for all vehicles and extracted from U.S. Energy Information Administration, All Motor Vehicles Fuel Economy, Table 8.1, retrieved from https://www.eia.gov/totalenergy/data/browser/?tbl=T01.08, June 14, 2023.

There are several additional variables included in later estimations. Vehicle horsepower and vehicle size measured as weight in pounds are extracted from US Environmental Protection Agency, 2022 EPA Automotive Trends Report, retrieved from www.epa.gov/automotive-trends/explore-automotive-trends-data, June 14, 2023. Household size as persons per household are derived from U.S. Census Bureau, Table HH-4, Households by Size, retrieved from https://www.census.gov/data/tables/time-series/demo/families/households.html, June 14, 2023. Finally, vehicle registration as an index (2015 = 100) is derived from Organization for Economic

Co-operation and Development, Passenger Car Registrations in United States [USASACRAISMEI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USASACRAISMEI, June 14, 2023.

Table 1 summarizes means and standard deviations of the variables after they have been converted to logarithms. The coefficient of variation (cv in the table) indicates that real gasoline prices and household size vary somewhat more around their means than do the other variables. Moreover, Table 2 shows that the variables are stationary in first differences (I(1)). This finding means that the PSS Bounds test proposed by Pesaran et al (2001) will be appropriate for testing whether these variables are cointegrated. Household size is an exception but the bottom two variables in the table are used as control variables only.

4. Results: The Role of VFE

4.1. The PY Specification

Table 3 summarizes the key results for several variations that focus exclusively on the role of the VFE variable. The approach shown in the first column shows estimates when VFE is excluded. It adopts the traditional price-income framework (*py* model) that explains consumption as a symmetric function of price and income increases and decreases. Unlike the analysis by Huntington (2010a; 2010b) and Dilaver and Hunt (2021) but similar to many other approaches, this particular model does not disaggregate the price responses into components like price maximums, price cuts and price recoveries. The remaining four specifications expands this regression to include an explicit technology variable represented by vehicle fuel efficiency (VFE). Column 2 results add the average vehicle fuel efficiency (VFE) trend. The remaining columns separate the VFE variable into one component representing changes induced by prices and another one representing responses to other factors like policy mandates. They differ from each other only by what other variables are used as additional controls.

The results in this table are based upon an unrestricted error-correction form of an autoregressive distributed lag (ARDL) equation that explains the change in per-capita gasoline consumption as a function of the change in all explanatory variables (indicated by the D. prefix) and the lagged levels of all variables (indicated by the L. prefix). One advantage of this reparameterized form is that short- and long-run responses are shown explicitly in the table. In this procedure, the delta method computes the corresponding standard errors for the long-run responses. Allowing a single annual lagged value for each variable initially, the dynamic specification supports an ARDL(1,0,1) *py* specification for consumption, prices and GDP in levels covering the 1948-2019 period. The additional lag for per-capita GDP allows for an adjustment to income to differ from that to prices. These estimates also incorporate a shift in the intercept for years prior to 1967.

The Breusch-Godfrey test fails to reject the null of no autocorrelation.[2] This finding allows the use of PSS Bounds test for cointegration that were referenced in the previous section. The specification includes an unrestricted intercept without a time trend (Case 3). Both the F and t tests reject no cointegration in this specification at the 1% level. The F-test significantly rejects the null of no relationship between the levels of the variables for the critical values provided by Kripfganz and Schneider (2020). The t-test for the lagged dependent variable rejects this hypothesis at the 1% level. Thus, these tests support the conclusion that the variables in this specification are cointegrated.

[2] These tests are based upon the STATA community-contributed ACTEST procedure with the robust option that is provided by Baum and Schaffer (2013). Note that the Cumby-Huizinga (Cumby and Huizinga, 1992) general test is performed for the fifth specification because gasoline prices are considered endogenous.

4.2. The VFE Trend

The analysis now shifts to estimates that include the VFE variable. Figure 1 shows that this VFE variable (in logarithms), denoted by a solid line and labeled on the left vertical axis, declines through the first several decades before rising sharply beginning in the late 1970s. This break in 1979 is very similar to the break in the estimated unobserved energy demand trend (UEDT) estimated by Dilaver and Hunt (2021) and reported in their Figure 5. Although the VFE variable and the Dilaver-Hunt UEDT estimates are not the same, their similar breaks suggest that their UEDT estimate appears to capture some of the missing VFE variable. However, their UEDT also incorporates other mobility and consumer tastes that are not included in the price and income variables. For the purposes of evaluating the direct rebound effect, it appears preferable to include the VFE variable explicitly rather than assume that the UEDT represents a valid proxy for the VFE trend alone.

Although the reversal in the VFE trend begins when gasoline price spiked during the 1970s (denoted by the dashed line and indexed on the right vertical axis), there appears to be a very limited relationship between these two trends. After 1980, real gasoline prices decline precipitously throughout the decade while VFE continues to rise sharply. In the post-1990 period, VFE continues to rise while prices fluctuate.

4.3. The VFE Specification

When VFE is added to the *py* model, multicollinearity between VFE and either prices or GDP does not appear to be a problem. Granger causality tests reject the hypothesis that price and GDP changes anticipate the movement in VFE when an exogenous dummy variable for years prior to 1979 is included with these three variables. These tests are based upon regressions where the AIC, HQIC and SBIC criterion all indicate that a single lag should be included.

Moreover, multicollinearity should enlarge the standard errors of the initial variables. However, adding VFE to a simple static equation with price and income levels leaves the standard error of the income variable unchanged and actually reduces the standard error of the price variable. Furthermore, the adjusted R-squared for gasoline consumption (0.901) in the static VFE equation is greater than its counterparts for price (0.160), GDP (0.810) and VFE (0.800) when each independent variable is explained by the others.

By contrast, the maximum price shown as the dashed line in Figure 2 suggests that it might play a role in the VFE trend. This variable is defined as the highest price between the initial year of the sample and the current year. It is equivalent to adding the initial year's price and the cumulative increase in the maximum price as used by Gately and Huntington (2002) and Dilaver and Hunt (2021). Huntington (2010) shows that this variable has both short and long run effects on gasoline consumption, while sub-maximum price changes have only short-run consequences.[3] Haughton and Sarkar (1996) find that maximum prices appear more relevant than actual prices in their evaluation of the U.S. gasoline tax.

The *vfe* estimates in the second column add the VFE variable and is an ARDL(1,0,1,0) model that incorporates an early-year shift (prior to 1968). It also supports the findings that the variables are cointegrated according to the PSS Bounds test. It differs from the initial specification (*py*) in the first column along several dimensions. The equation appears slightly more powerful. The log-likelihood ratio and adjusted R-squares are higher and the root-mean-squared-error is lower. The adjustment to the long-run equilibrium is almost twice as fast with VFE than without VFE. As a result, short-run price elasticity is greater (-0.032 rather than - 0.024) while long-run price elasticity is less (-0.127 rather than -0.176). There is no significant

[3] Figure 2 also shows that the maximum price plays a critical role in shaping VFE and hence the long-run response to gasoline prices.

long-run response to real GDP in the *py* specification, but short-run (SR) responses to real GDP in both specifications appear comparable at approximately 0.5. Figure 3 compares the residuals from the *py* and *vfe* specifications. The principal differences appear in the mid-1970s and late-1980s when the *vfe* residuals appear closer to zero. Overall, it appears that the inclusion of the VFE variable contributes modestly to an improved analytical fit.

Policymakers are primarily interested in whether VFE reduces energy use in the long run. The long-run response to the VFE trend in the *vfe* specification equals -0.800 and appears significant at the 1% level. This response means that actual consumption reduces by 80% of the initial VFE of the automobile stock. The countering direct rebound effect accounts for the remaining 20%. This estimate is highlighted and reported at the bottom of Table 3. In this case, these findings are consistent with many previous studies of the rebound effect associated with VFE and gasoline consumption that were discussed in the literature review section.

Although this long-run point estimate for the VFE coefficient (-0.800) statistically differs from zero, the potential effect (-1) lies just barely above the lower value (-1.096) of this coefficient's 95% confidence interval. Thus, the estimated coefficient is not statistically different from the potential effect. This finding is shown as the insignificant F-statistic shown in the F(LR.vfe=-1) row of the table. Moreover, the additive inverse of the direct effect (-0.200) is not significantly different from the long-run price elasticity (-0.127) for gasoline in this equation. The insignificant F-statistic labeled F(LR.vfe-1=p) in the table summarizes this finding. Although statistically equal to each other, the point estimate of the rebound effect is almost 60% higher than its counterpart for the price effect.

4.4. Some Extensions

Many of the results for the *vfe* specification are carried over to the other versions in this table that treat the VFE variable differently. Price-induced adjustments in VFE may influence gasoline demand differently than those imposed by mandates and other factors unrelated to price. To account for this possibility, the effect of VFE is separated into endogenous responses to the maximum price and exogenous policy shifts by using a separate unobserved components model explaining the VFE trend. The approach enters the maximum gasoline price as an exogenous variable and derives an unobserved trend component where the intercept term follows a random walk. This trend is viewed as exogenous to the model and not explained by maximum prices. Figure 4 displays the unobserved trend. Key results from this unobserved components model are summarized in the appendix.

Maximum prices and policy-induced VFE improvements as derived above are entered as separate variables in the last three specifications of Table 3. Compared to the *vfe* specification, these estimates show that separating price-induced from non-price-induced responses does not materially affect the response to VFE. By itself, separating the VFE variable lowers the long-run direct rebound effect to 0.154 as shown in the *vfexp* column. Adding household size to this specification results in a long-run direct rebound effect of 0.171 in the *vfehh* version. The negative coefficient for household size is consistent with households that have more people will make more multi-person trips, thereby decreasing gasoline consumption on a per-capita basis. Replacing household size with automobile registrations returns a value of 0.197 or the long-run direct rebound effect in the *vferg* equation.[4] A third but unreported alternative considered congestion as proxied by the ratio of vehicle registrations per miles of roadway. Greater

[4] These variables are entered separately in order to mitigate collinearity in the explanatory variables. Both variables are insignificant if they are both included in the same regression.

congestion could potentially increase or decrease gasoline consumption, depending upon how more gallons per mile used in slower traffic compares with fewer miles driven along more congested roads. This variable was not significant and did not influence the direct rebound effect. Based upon these results, the previous estimate of 0.200 appears relatively robust across different approaches. The long-run response to maximum price is considerably larger than its counterpart to gasoline prices, particularly in the last two specifications.

5. Results: Adding Controls for Other Vehicle Attributes

When policy mandates imposed greater VFE in the late 1970s, the automobile industry transformed vehicles in many other respects. Two important developments were greater vehicle horsepower and the increased vehicle weight associated with larger passenger and cargo space. Higher horsepower requires more gasoline when families drive their vehicles under normal leisure conditions (Natural Resources Canada, n.d. a). Heavier vehicles increase gasoline consumption through more inertia and extra friction between the road and wheels, if other factors are held constant (Natural Resources Canada, n.d. b). Moreover, heavier vehicles with additional space may encourage extra or longer trips and more driving. Excluding other vehicle attributes from the results in Table 3 could cause some of their omitted effects to be incorporated by other variables including the VFE trend. Given the high collinearity between VFE, weight and horsepower, it is best to introduce weight and horsepower separately.

5.1. Vehicle Weight and Horsepower

When weight (horsepower) is added to the *vfe* specification, the results are shown in the *vfew* (*vfehp*) column of Table 4. Although data availability for the weight and horsepower variables restrict the estimation to a smaller sample (1975-2019), both the short-run and long-run responses to gasoline prices are similar to their *vfe* counterpart. Similar to the *vfe* specification, the Breusch-Godfrey tests do not reject the absence of autocorrelation and the Bounds tests confirm cointegration.

Some important differences do exist. The adjustment to long-run equilibrium appears faster in these two columns than in their *vfe* counterpart of Table 3. The long-run GDP elasticities are no longer significant, most likely because the vehicle attributes are stronger explanatory variables than income. Short-run GDP responses are lower at approximately 0.33 rather than 0.50. However, the most relevant new result is the higher long-run direct rebound effect highlighted at the bottom of Table 4.

When weight (horsepower) enters as an additional control variable, the long-run direct rebound effect is 0.515 (0.411). Underlying these findings is the fact that VFE happened at the same time that vehicle weight and horsepower were also increasing and that these other attributes also influenced the value of driving or gasoline consumption directly. When these other adjustments are controlled, the direct rebound effect appears to be at least twice as large as those estimated for the *vfe* specification above. The row labeled F(LR.vfe=-1) indicates that the long-run VFE coefficient for the *vfew* and *vfehp* versions is statistically different from -1 at the 5% and 10% level, respectively. As the literature review section of this paper discusses, this higher rebound effect could be due to households valuing a range of factors other than the monetary cost savings from energy efficiency. It may also reflect that consumers view their changes in their equipment stock as long-term transformations rather than as simple responses to cyclical price fluctuations where price changes often reverse themselves.[5]

[5] For example, households could purchase homes further from their work locations because they view the cost savings for transportation to be relatively permanent.

5.2. Endogenous Price

The third specification in Table 4 is a two-stage least squares estimate that allows the real gasoline price to be endogenous. This *inst* specification is based upon the *vfehp* equation that includes both VFE and horsepower. A reverse causality may exist where shifts in the US gasoline demand curve are influencing gasoline prices. As a result, the observed price and quantity may not be tracing out a demand function. The most direct approach for developing estimates comparable to the *vfehp* equation would be to apply an instrumental variable that correlates strongly with U.S. gasoline prices but weakly with U.S. gasoline consumption. Instrumental variables can be used to develop first-stage estimates of the gasoline price, which can then be inserted into the function explaining domestic gasoline demand curve to adjust for this problem and mitigate the potential bias from this reverse causality.

U.S. gasoline prices are closely linked to the world crude oil price path. Reasonable instruments for gasoline prices, therefore, most likely relate to factors that shape world crude prices. Two influential factors that have increased crude oil prices throughout much of the post-World-War-Two era include stronger world economic growth and the decline and eventual recovery of the relatively inexpensive U.S. crude oil supplies. The oil supplies available for the U.S. gasoline market are the residual supplies that are not consumed within the United States. Therefore, domestic oil supplies decline and petroleum prices increase not only when the share of global supplies originating within the United States declines but also when foreign economies grow more vigorously than the U.S. economy. For this reason, the selected instrumental variable measures the difference between the share of GDP output attributable to all economies outside the OECD nations and the share of global supplies originating from the United States. The share contributed by other mature OECD countries are excluded from this instrumental variable because their economic growth is likely to be highly correlated with U.S. economic growth through common institutions, policies and international trade. This high correlation means that overall OECD growth could influence both the residual oil supply as well as the U.S. economic growth explaining U.S. gasoline demand.

Data on U.S. and global petroleum supplies were derived from BP Statistics World Energy Statistics.[6] Data on the LDC share of GDP were derived from World Bank.[7] Figure 5 displays both shares as well as the difference between the two shares. The market gap share (the instrumental variable indicated by the thick solid line) begins to increase in the mid-1980s as U.S. production share declines. After 2000, the rising LDC share escalates the market gap share. The oil shale revolution just prior to 2010 increases the U.S. production share, which tends to soften the rate at which the market gap share increases.

It is expected that the price elasticity of gasoline prices under these conditions will be higher than when prices are assumed to be exogenous. When gasoline prices are viewed as exogenous, unobserved upward shifts in the demand curve will expand both observed prices and gasoline consumption, making the slope of the demand curve appear to be less responsive to price. Both the short-run and long-run price elasticities are significant but only modestly larger in the *inst* specification than their counterparts in the *vfehp* equation.

Excluding the instrumental variable from the initial round produces an F-test equal to 29.24, which far surpasses the commonly used threshold of 10 for a suitable instrument. However, one cannot reject the null that price is an exogenous variable. Both the Durbin (score)

[6]The 2021 edition is available at https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2021-full-report.pdf.

[7] Available at https://data.worldbank.org/.

χ^2 (0.297) and the Wu-Hausman F-test (0.246) are insignificant. With one endogenous variable and one instrumental variable, the gasoline demand equation is exactly identified.

Long-run responses to VFE are similar in nature to the exogenous estimates although they appear closer to unity. At -0.683, the point estimate for this response is not significantly different from the potential response of -1. The corresponding direct rebound effect is 0.317 rather than 0.411 in the exogenous estimate but it remains above the estimate of -0.200 in Table 3. The additive inverse of this direct effect is not significantly different from the long-run price elasticity (-0.126) for gasoline in this equation.

5.3. *Recursive VFE Estimates*

The last column of Table 4 (the *recursive* specification) reports results when VFE is estimated recursively in the first round before its fitted values are entered in the gasoline equation.[8] The first stage uses the lagged value of VFE, maximum gasoline price, and the current and lagged values of per-capita GDP. This version produces a long-run direct rebound effect of 0.496. Estimating the vehicle fuel efficiency and gasoline consumption equations as seemingly unrelated regressions altered the results very little. The χ^2 statistic in the Breusch-Pagan test of 0.097 failed to reject the hypothesis that the residuals in the two equations were independent.

6. Backcasting 1978-2019 Under Alternative Conditions

Figure 6 provides a visual summary of the direct rebound effect over the 1978-2019 period based upon dynamic backcasts of the *vfehp* equation reported in the second column of Table 4. Exogenous variables include both VFE and vehicle horsepower among other variables

[8] This recursive approach incorporates minor adjustments to the coefficient standard errors.

in this specification. The thick solid line displays the fitted values for the actual per-capita gasoline demand trends expressed in logarithms. It incorporates improvements in both VFE and vehicle horsepower. Enacted in 1975, US corporate average fuel efficiency standards (CAFE) began raising miles per gallon in vehicles in 1978.

6.1. VFE Improvements

Estimating the effects of improving VFE requires a counterfactual where these improvements do not materialize. If these improvements are omitted and the VFE trend remains at its 1978 level, gasoline demands based upon this equation would be uniformly raised to the thin solid line in this figure. Therefore, the effect of imposing VFE would be the distance (in logarithms) between these two lines. The closer the actual solid thick line is to the counterfactual solid thin line, the smaller will be the net response to VFE improvements and the larger will be the offsetting direct rebound response. By 2019, estimated per-capita gasoline demand due to the VFE improvement in this figure would have been 22.4% lower than the counterfactual level without any VFE.

This response will be less than what would be expected if gasoline consumption declined by the same percent as VFE. Gasoline consumption associated with this potential effect without any rebound effect would lie upon the dashed line in this figure. This projection is constructed by lowering the estimate in the higher solid thin line in any year indicating no VFE improvements by the percentage change in the VFE trend from its 1978 level. The closer the solid thick line is to the dashed line, the smaller will be the offsetting direct rebound response. The distance between the higher solid thin line and the dashed line represents the potential decrease in per-capita gasoline demand in the absence of any direct rebound effect. By 2019, potential gasoline demand would be expected to fall below the higher solid thin line by 38.6%. Thus, the implied direct rebound effect by 2019 would be 1 – (22.4%/38.6%) = 42.0% of potential demand adjustments. This rebound adjustment is closely aligned with the long-run elasticity of VFE (41.1%) revealed in the *vfehp* specification in column 2 of Table 4.

6.2. VFE and Horsepower Improvements

Putting aside the indirect rebound effects that may influence energy use in other energy service demands or sectors, does this estimate tell policymakers how much energy use is saved within automobile travel by policy mandates on VFE? It depends. The results displayed in Figure 6 are based upon the conjecture that policy mandates change only fuel efficiency without altering other vehicle attributes. This assumption appears unrealistic because automobile producers are in the business of selling vehicles that serve a variety of purposes. They are unlikely to sell nearly as many cars if their only response to mandated efficiency improvements would be to manufacture the identical automobile that now meet the energy efficiency requirements. Introducing fuel efficiency requires a comprehensive reconfiguration of the vehicle stock that can fundamentally change the energy-using capital stock over a number of years. Mandates restrict fuel efficiency but they do not impose other constraints on other vehicle attributes. Since 1977, car makers have made vehicles that not only improve fuel efficiency but also add other services like passenger and cargo space, weight and horsepower. Modifications in these vehicle traits can lead to a "multi-attribute leakage" effect that allows for a larger "snapback" or rebound response.[9]

Figure 7 duplicates the general approach used for constructing Figure 6, but the thin solid line now removes both the VFE and horsepower improvements from what actually happened.

[9] Obviously, whether other attributes lead to more or less energy use will depend upon the energy service being evaluated.

This adjustment allows the direct rebound effect to incorporate not only VFE but also changes in vehicle horsepower. By 2019, the distance between the higher thin line and the thick line represents an 11.6% decrease in per-capita gasoline demand due to VFE improvements. The removal of any VFE effects should increase potential gasoline consumption by the same 38.6% in 2019 as above if there was no rebound effect. This potential effect is represented by the distance between the thin and dashed lines. In this case, the implied direct rebound effect by 2019 would be considerably larger than above (about two-thirds higher) and equal to 1 – (11.6%/38.6%) = 69.9%. Without any restrictions on other vehicle traits, the energy efficiency mandate is made less effective in reducing gasoline consumption. Note that this higher direct rebound effect incorporates only a change in technology attribute and does not depend upon indirect rebound adjustments occurring outside of the vehicle production industry.

6.3. Flexible Price Path

The previous backcasts are based upon holding all other variables including the real gasoline price at their actual levels for the 1978-2019 period. The *inst* specification shown in the third column of Table 3 allows both the gasoline consumption and price to be endogenous. Backcast estimates are derived using the first-round equation for real gasoline price and the instrumental specification for the endogenous real price variable in determining per-capita gasoline consumption. Removing the VFE improvements from what actually happened had a surprisingly important impact on real gasoline prices. Figure 8 shows that prices without VFE improvements (thin solid line) would have been substantially above the levels that actually happened (thick solid line). These pronounced effects appear consistent with the small price elasticity that are often estimated using annual time series.

Figure 9 shows comparable estimates for actual, potential and no-VFE per-capita gasoline consumption if prices are allowed to be flexible rather than tied to their actual levels. Unexpectedly, flexible prices produce similar results to those in Figure 7 where the rebound effect also includes vehicle horsepower and price is held fixed at actual levels. By 2019, the distance between the higher thin line and the thick line in Figure 9 represents an 11.6% increase in per-capita gasoline demand from actual levels due to removing any VFE effects. The corresponding rebound effect would be 69.9% of the potential effect.[10] Figure 10 summarizes the results in this section by comparing the 2019 direct rebound effect for the three sets of backcasts.

7. Conclusion and Policy Insight

Data availability and other constraints frequently make it difficult to represent technology factors that in addition to real prices and economic activity help shape energy demand trends. Through a range of alternative specifications that incorporate vehicle fuel efficiency (VFE), this analysis underscores a common conclusion about the direct rebound effect of improved vehicle fuel efficiency on U.S. gasoline consumption. The long-run direct rebound effect has a larger impact on gasoline use than does the change in gasoline prices over the long run. Although the differences in the point estimates for rebound and price effects are large, they are not always statistically different from each other, particularly in the lower range.

The long-run direct rebound response in this analysis typically ranges between 20% and 50% of the potential effect. Lower estimates are associated when regressions use VFE as the lone technical attribute along with price and GDP. When analysis also includes horsepower or vehicle weight as control variables, higher estimates occur. Replacing fixed gasoline price paths with

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[10] Although these results for the rebound effect in 2019 appear identical to the estimates for the VFE+HP scenario (Figure 7), these similar impacts are by chance. They differ in other years. For example, the direct rebound effect in 2000 is 70.2% in Figure 9 compared to 56.1% in Figure 7.

endogenous prices appears to lower this rebound effect to about 30%, but this finding should be viewed cautiously. This equation has noticeably lower explanatory power, and tests for exogeneity reveal that U.S. price may not be endogenous. As a general rule, the standard practice of linking rebound effects to price elasticities will understate the direct rebound effect. A useful extension would be to apply this framework to other energy service demands when data on the energy-using equipment are readily available.

One can only surmise the reasons for this understatement without further empirical research. Most price changes have little in common with what happens when VFE modifications permanently change the cost per mile driven. As previous research has indicated (see the literature review in section 2.3), capital stock modifications are long-run adjustments that permanently change the costs. These conditions contrast with the response to cyclical gasoline price fluctuations where price changes in one period can be reversed in the near future.

When policymakers mandate energy efficiency standards, they may anticipate that energy consumption and pollution levels will be less by a comparable amount. Addressing this issue with a narrow definition of the direct rebound effect can be seriously misleading in certain situations. Direct rebound effects can rise above 50% if the VFE estimates also control for other vehicle attributes like vehicle size, weight and horsepower. Simulations based upon this paper's empirical estimates imply a long-run direct rebound effect equal to 70% when car makers respond to VFE mandates by modifying other vehicle attributes. These impacts appear comparable to simulations showing the response to VFE improvements (without any additional horsepower) when gasoline prices are flexible rather than having its path fixed in time. Although lower gasoline prices increase gasoline consumption through the rebound effect, they also provide important welfare improvements that may be underappreciated.

Another useful extension of this approach would be to apply it to other energy service demands where “multi-attribute” leakage effects might exist. Possibilities here include energy efficiency improvements in computers and electronics that augment energy consumption by rearranging household tasks such as online shopping, arranging travel, and banking transactions (Galvin, 2015). Another prominent example would be the shift in the power generation industry towards more energy-efficient combined-cycle natural gas plants. This technology not only reduces energy costs but also makes these plants more competitive in a new market as a replacement for coal and nuclear baseload generation rather than for peaking purposes only (US Energy Information Administration, 2016). These factors may cause an additional “snap back” that augments energy consumption.

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Table 1. Data Summary

variable	obs	mean	sd	cv	max	min
Gasoline	73	3.28	0.19	0.058	3.51	2.69
GDP	73	10.33	0.43	0.042	10.96	9.56
Price	73	4.93	0.35	0.072	5.71	4.32
VFE trend	71	2.68	0.16	0.058	2.90	2.48
Weight	45	8.22	0.09	0.011	8.33	8.07
Horsepower	45	5.10	0.28	0.055	5.50	4.63
_____						
Maximum Price	73	5.30	0.38	0.071	5.71	4.72
Household size	60	1.02	0.09	0.093	1.21	0.92
Registrations	60	4.70	0.20	0.042	5.02	4.14

Notes:
Logarithmic levels, full sample (73 obs) 1947-2019.
CV, coefficient of variance, equals standard deviation (sd) divided by mean.

Table 2. Unit Root Tests

	Levels		Differences	
	Lags	**τ**	**Lags**	**τ**
Gasoline	1	-0.519	1	**-2.656*****
Income	1	-1.615	1	**-5.812*****
Price	1	-2.656	1	**-5.381*****
VFE Trend	1	-1.093	0	**-3.383*****
Horsepower	1	-1.550	1	**-2.861*****
Weight	2	-1.607	1	**-3.441*****
Maximum Price	3	-2.030	1	**-2.723*****
Household Size	3	-1.646	2	-1.194
Registrations	1	-2.028	1	**-4.023*****

Notes:
Significant statistics are boldfaced.
*** denotes $p<0.01$, ** denotes $p<0.05$; * denotes $p<0.10$.
Augmented Dickey-Fuller tests based upon a generalized least-squares regression.
Minimum Schwarz information criteria determined number of lags.

Table 3. Estimated Coefficients and Statistics for Equations With and Without VFE

	py	vfe	vfexp	vfexphh	vfexprg
	b/se	b/se	b/se	b/se	b/se
ADJ					
L.Gasoline	-0.138***	-0.251***	-0.229***	-0.224***	-0.167***
	(0.026)	(0.039)	(0.045)	(0.058)	(0.037)
LR					
L.Price	-0.176***	-0.127***	-0.090***	-0.118***	-0.125***
	(0.058)	(0.029)	(0.030)	(0.033)	(0.043)
L.GDP	-0.016	0.409***	0.409***	0.329**	0.552***
	(0.069)	(0.081)	(0.097)	(0.139)	(0.134)
L.VFE trend		-0.800***	-0.846***	-0.829***	-0.803**
		(0.148)	(0.249)	(0.272)	(0.366)
L.Maximum Price			-0.184***	-0.392***	-0.307***
			(0.061)	(0.077)	(0.079)
SR					
D.Price	-0.024***	-0.032***	-0.021***	-0.027***	-0.021***
	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)
D.GDP	0.505***	0.495***	0.469***	0.341***	0.266***
	(0.100)	(0.092)	(0.090)	(0.078)	(0.090)
D.VFE trend		-0.201***	-0.194**	-0.186***	-0.134**
		(0.053)	(0.077)	(0.063)	(0.065)
D.Maximum Price			-0.217***	-0.295***	-0.282***
			(0.048)	(0.039)	(0.037)
L.D.Maximum Price				0.076**	0.084**
				(0.037)	(0.037)
Household size				-0.284*	
				(0.166)	
Registration					0.025*
					(0.014)
pre1967	-0.040***				
	(0.011)				
pre1968		-0.041***	-0.043***	-0.024**	-0.024**
		(0.011)	(0.012)	(0.010)	(0.010)
Constant	0.607***	0.469***	0.480***	1.222**	0.110
	(0.109)	(0.118)	(0.124)	(0.579)	(0.148)
Observations	72	71	69	60	60
Log-Like	190.660	194.558	198.226	195.152	195.351
Adj_R^2	0.594	0.647	0.707	0.805	0.807
RMSE	0.018	0.016	0.015	0.010	0.010
Breusch-Godfrey#	0.045	0.077	0.567	0.299	0.037
Case	3	3	3	3	3
Bounds_F	16.226***	16.713***	11.388***	6.085***	14.453***
Bounds_t	-5.328***	-6.498***	-5.049***	-3.841*	-4.463**
F(LR.vfe=-1)		1.82	0.38	0.39	0.29
F(LR.vfe-1=p)		0.23	0.06	0.03	0.03
LR_Rebound		0.200	0.154	0.171	0.197

Notes:
* p<0.10; ** p<0.05; *** p<0.01
All variables are in logarithms.
Lagged levels are denoted by L. prefix.
First-differences are denoted by D. prefix.
Samples: annual, 1948 – 2019; and annual, 1960 – 2019.
Cumby-Huizinga replaces Breusch-Godfrey test due to endogenous price in the *inst* specification.

Table 4. Estimated Coefficients and Statistics for Equations With Other Vehicle Attributes

	vfew b/se	vfehp b/se	inst b/se	recursive b/se
ADJ				
L.Gasoline	-0.326***	-0.308***	-0.330***	-0.306***
	(0.072)	(0.073)	(0.088)	(0.078)
LR				
L.Price	-0.107***	-0.115***	-0.126***	-0.109***
	(0.027)	(0.029)	(0.036)	(0.028)
L.GDP	0.128	0.047	0.128	-0.022
	(0.154)	(0.211)	(0.245)	(0.215)
L.VFE trend	-0.485*	-0.589**	-0.683**	-0.504**
	(0.248)	(0.238)	(0.283)	(0.237)
L.Weight	0.335**			
	(0.158)			
L.Horsepower		0.195*	0.164	0.220*
		(0.105)	(0.114)	(0.109)
SR				
D.Price	-0.035***	-0.035***	-0.041***	-0.033***
	(0.008)	(0.008)	(0.014)	(0.008)
D.GDP	0.330**	0.324**	0.302**	0.344**
	(0.126)	(0.128)	(0.144)	(0.128)
D.VFE trend	-0.158*	-0.181*	-0.225*	-0.154
	(0.093)	(0.090)	(0.124)	(0.092)
D.Weight	0.109**			
	(0.047)			
D.Horsepower		0.060**	0.054	0.067**
		(0.028)	(0.033)	(0.028)
Constant	0.370	1.254***	1.221***	1.353***
	(0.262)	(0.371)	(0.409)	(0.362)
Observations	45	45	45	45
Log-Like	131.074	130.631	126.701	129.924
Adj_R^2	0.546	0.537	0.449	0.523
RMSE	0.014	0.014	0.016	0.015
Breusch-Godfrey	2.163	2.649	1.469	2.649
Case	3	3	3	3
Bounds_F	7.679***	7.382***	4.981**	6.918***
Bounds_t	-4.511**	-4.228**	-3.748*	-3.892*
F(LR.vfe=-1)	4.29**	2.98	1.25	4.28**
F(LR.vfe-1=p)	2.43	1.39	0.39	2.40
LR_Rebound	0.515	0.411	0.317	0.496

Notes:
* p<0.10; ** p<0.05; *** p<0.01
All variables are in logarithms.
Lagged levels are denoted by L. prefix.
First-differences are denoted by D. prefix.
Sample: annual, 1975 – 2019.

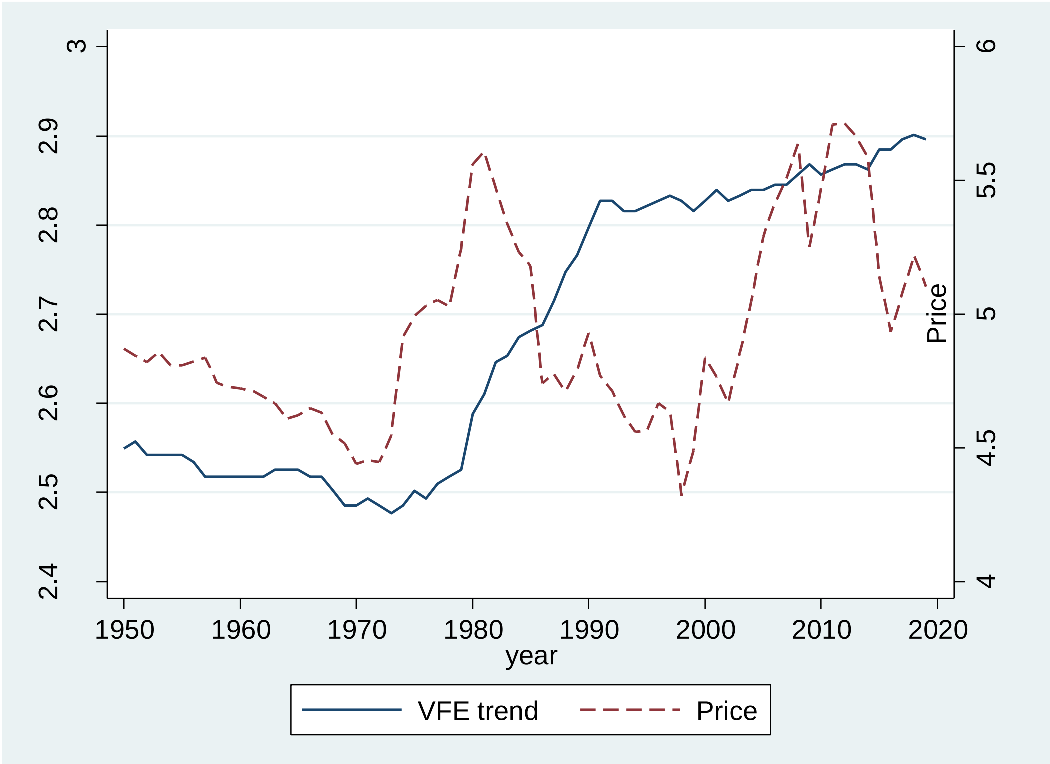

Figure 1. VFE and Gasoline Price Trends

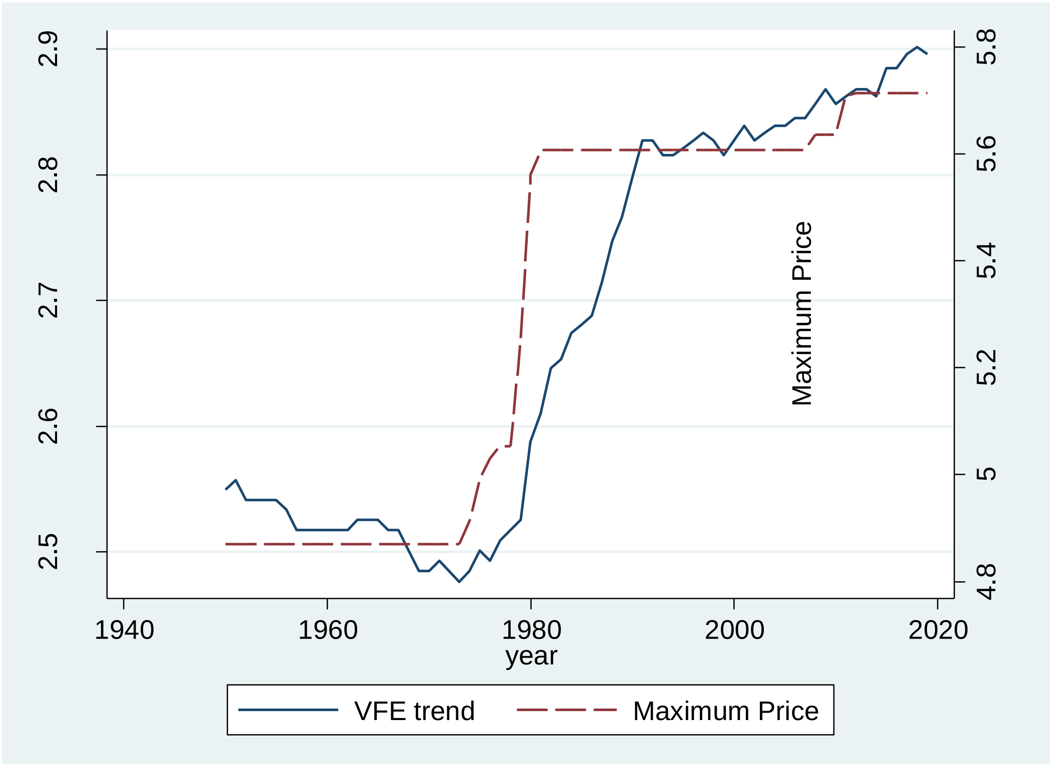

Figure 2. VFE and Maximum Gasoline Price Trends

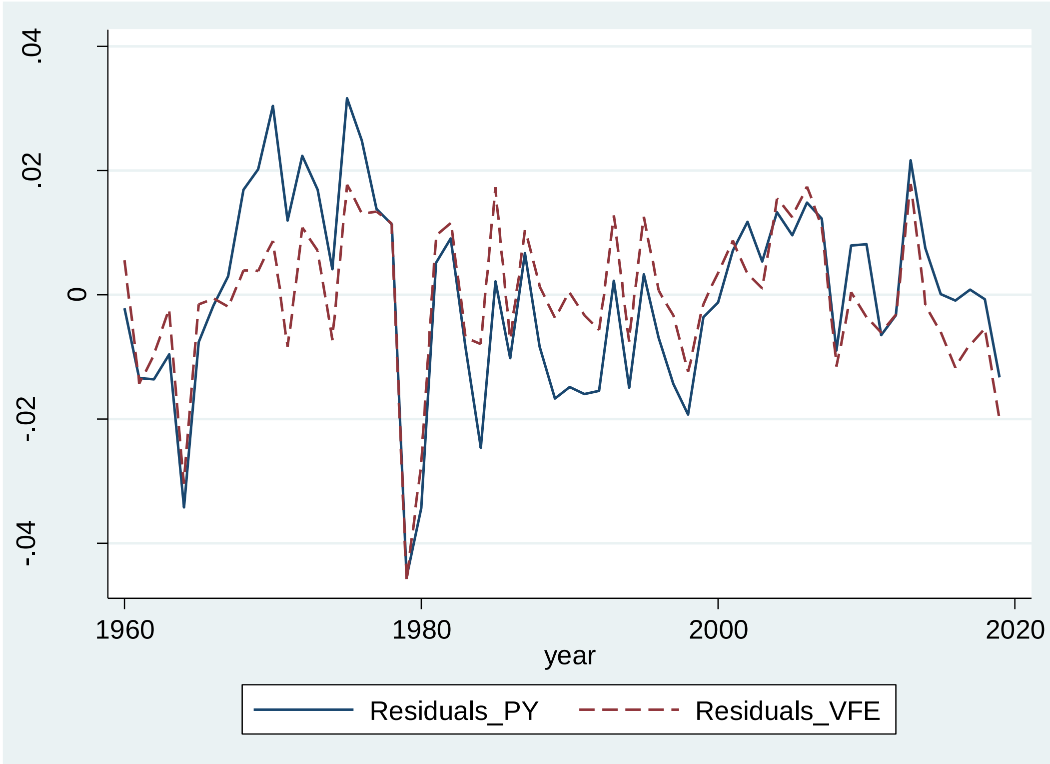

Figure 3. Residuals for PY and VFE Models

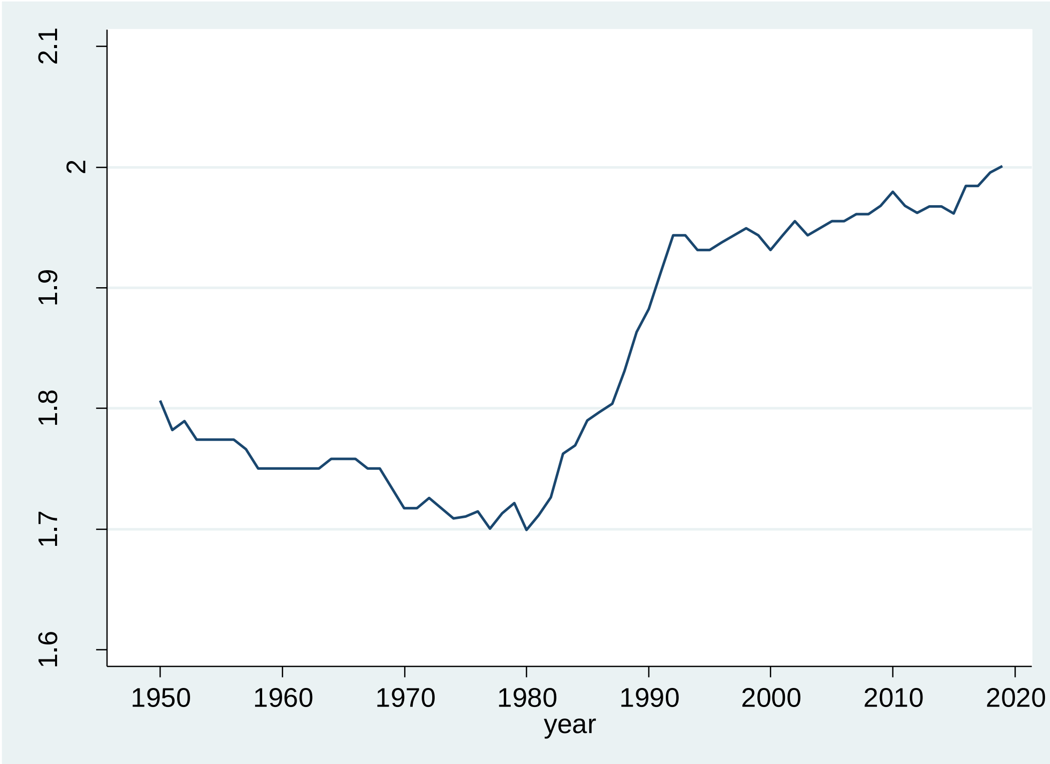

Figure 4. The unobserved VFE trend after adjustments for maximum price

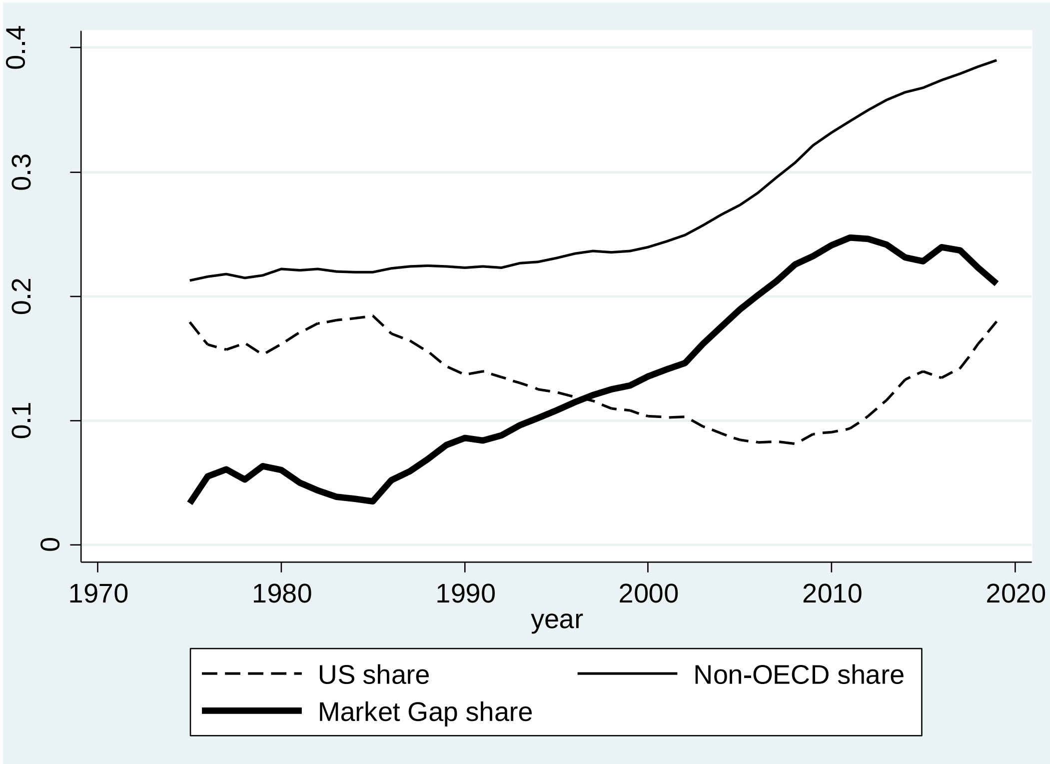

Figure 5. Market Gap share (instrumental variable)

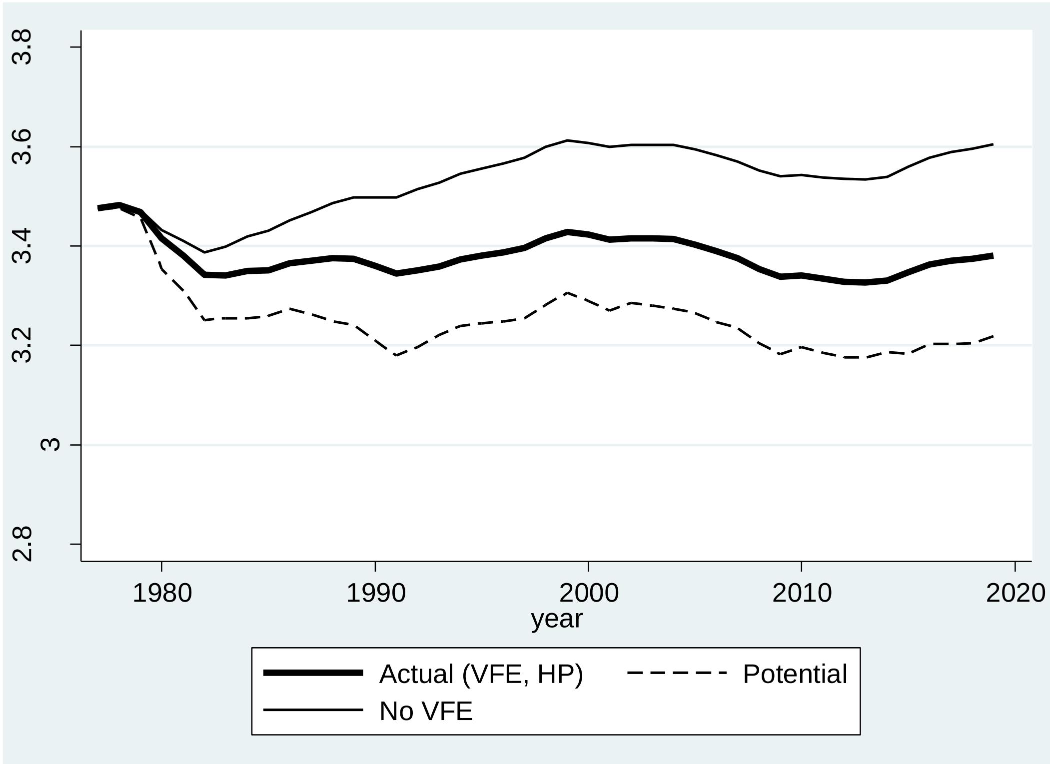

Figure 6. US Gasoline Consumption with VFE Alone and Fixed Prices

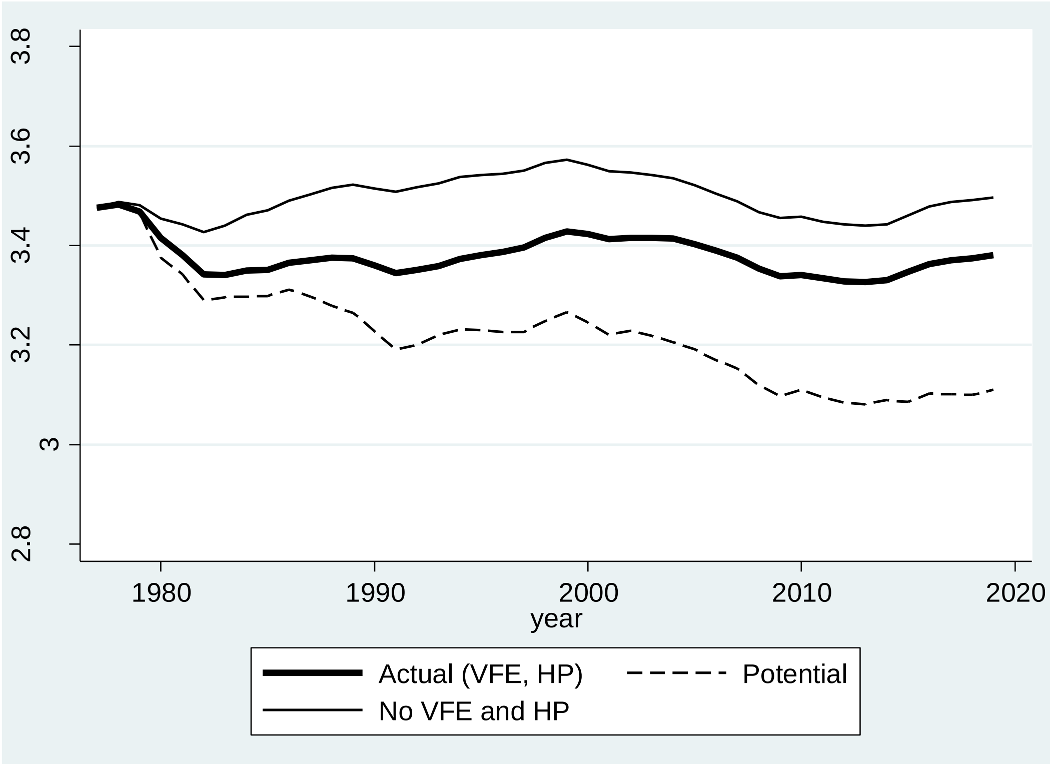

Figure 7. US Gasoline Consumption with VFE + HP and Fixed Prices

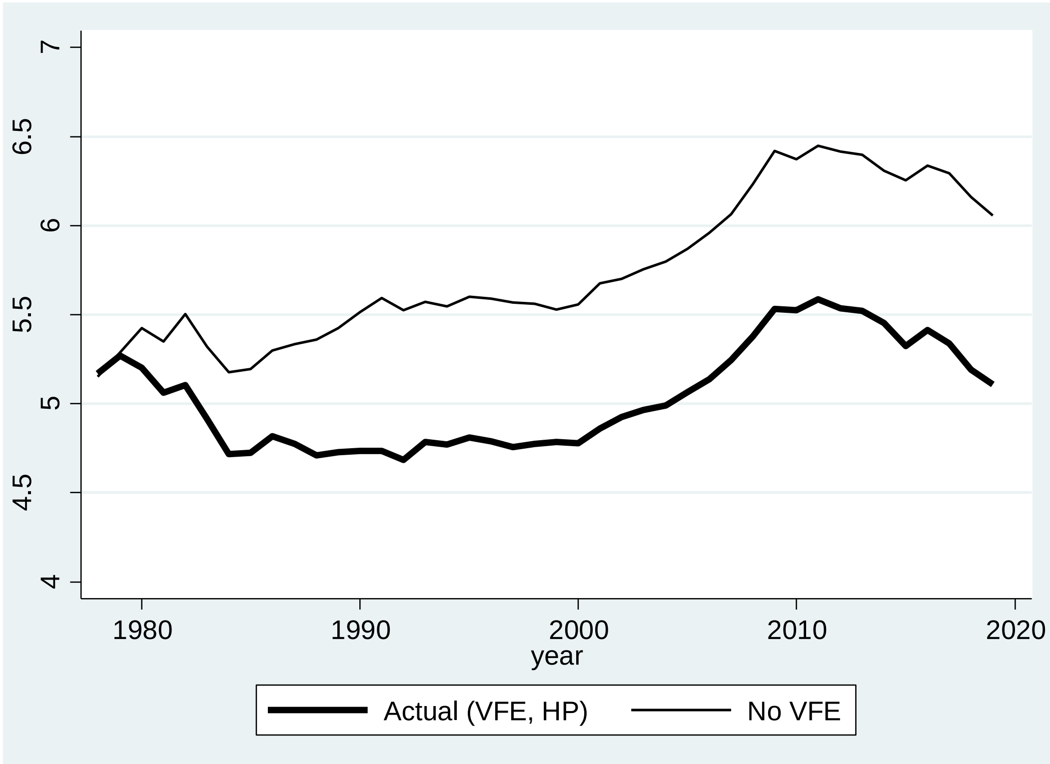

Figure 8. US Gasoline Price (in logarithms)

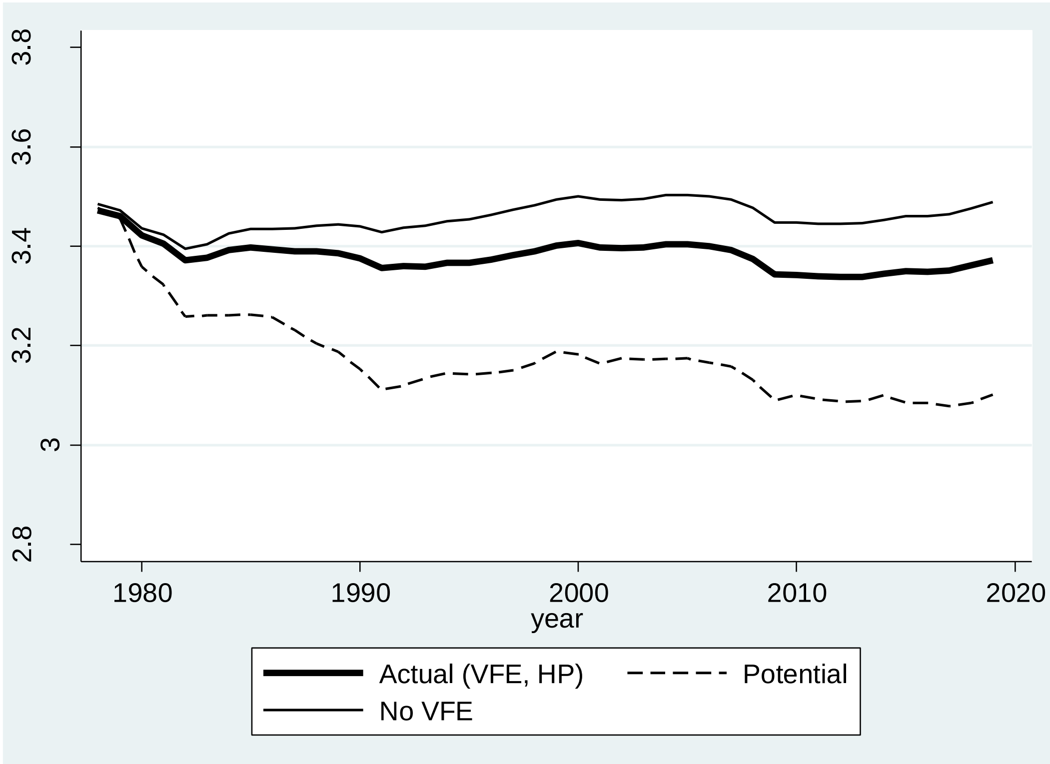

Figure 9. US Gasoline Consumption with VFE Alone and Price Rebound

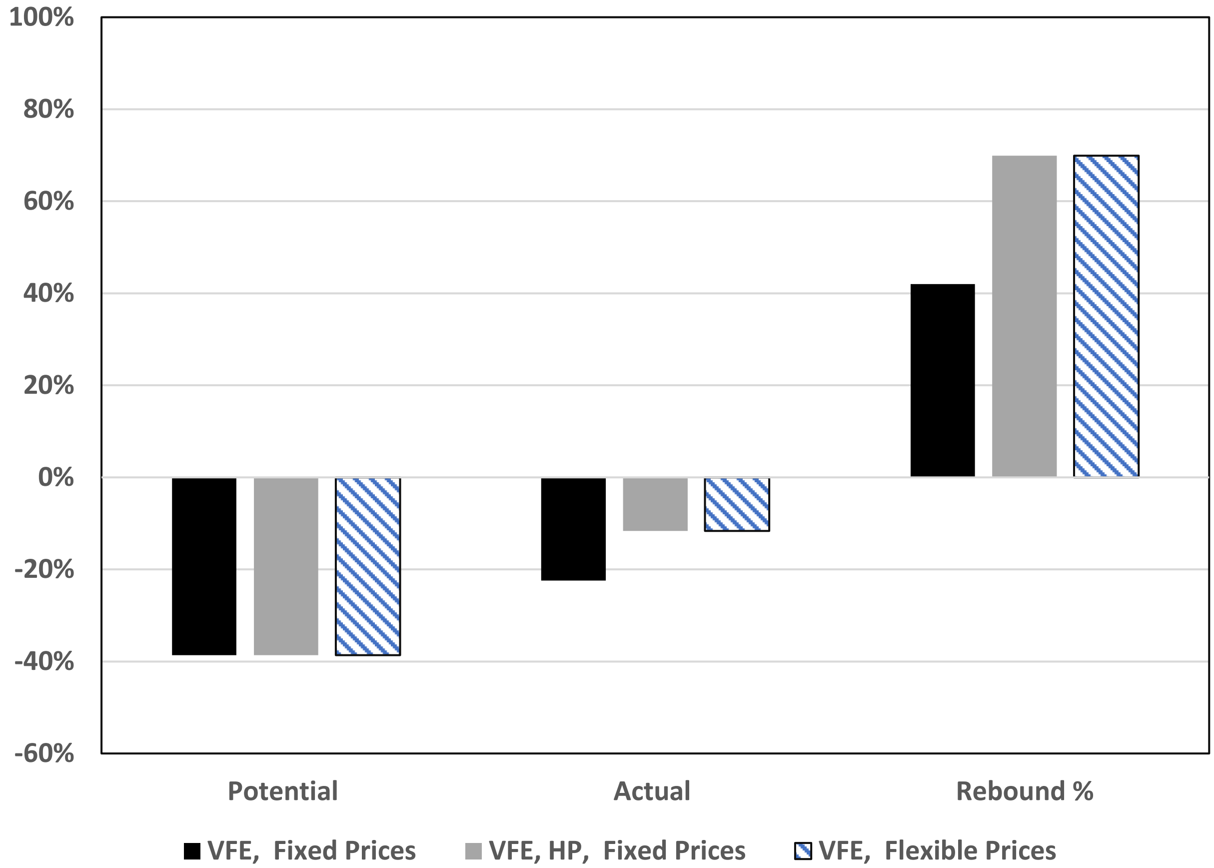

Figure 10. US Gasoline Rebound Effect (% of Potential) in 2019

**Notes: Potential and Actual show the percent difference in the 2019 levels.
Rebound % equals 1 – (Actual/Potential).**

Appendix: Model for Determining Exogenous Policy VFE Trend

Figure 4 in the main text shows the main result from the unobserved component model for separating the exogenous policy effect from the influence of maximum gasoline prices. This policy VFE trend is discussed more extensively there.

Table A-1 provides more details about the estimated model itself, including the coefficients, standard errors, and two widely used information criteria.

Table A-1: Model for Determining Exogenous Policy VFE Trend

```
Unobserved-components model
Components: random walk

Sample: 1949 - 2019

Log likelihood    =     205.19
Number of obs     =         71
Wald chi2(1)      =      23.79
Prob > chi2       =       0.00

-----------------------------------------
       lnVFE |      Coef.   Std. Err.
-------------+---------------------------
  lnpgas_max |   .1575972   .0323118
-------------+---------------------------
   var(level)|   .0001622   .0000274
-----------------------------------------
Akaike's information criterion   -406.38
Bayesian information criterion   -401.85
```