The Effects of New-Vehicle Price Changes on New- and Used-Vehicle Markets and Scrappage

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Assessment and Standards Division
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EXECUTIVE SUMMARY

The U.S. Environmental Protection Agency (EPA) sets emission standards for new light-duty vehicles (LDVs), with existing vehicles generally not expected to meet the same standards. Typically, these standards are expected to increase the up-front costs of new vehicles, may affect vehicle operating costs (e.g., through changes in fuel economy), and are likely to affect new-vehicle sales because of their effects on new-vehicle prices and characteristics. In addition, given substitutability between new and used vehicles, changes in new-vehicle prices, sales, and operating costs are likely to affect the market for used vehicles. Changes in the valuation of used vehicles are, in turn, likely to affect vehicle scrappage rates. As part of regulatory analyses, EPA often seeks to characterize these effects and interactions between new- and used-vehicle markets and scrappage. Consumer response to changes in vehicle prices and characteristics induced by regulatory policy has important implications for the total size and average age of the U.S. vehicle inventory, influencing net impacts of regulatory actions on greenhouse gas and criteria pollutant emissions, vehicle safety, and other outcomes. Improving our understanding of such interactions at the aggregate level is important for transportation policy analyses.

This study had three major goals. The first was to develop a theoretically sound methodology for characterizing the aggregate U.S. LDV inventory and the pathways through which regulatory policy or other scenarios could affect the distribution of the entire vehicle inventory. The second was to conduct a detailed literature review to identify studies providing estimates of the values of several elasticities important for modeling U.S. vehicle markets and vehicle inventory in a manner consistent with the theoretical model and to synthesize available estimates. The third was to develop and parameterize an aggregate simulation model consistent with the theoretical framework and the existing data available from the literature and implement the model to explore the implications of alternative scenarios for U.S. vehicle markets.

We developed a theoretical model of the relationships between new- and used-vehicle markets, scrappage, and total inventory at an aggregate level for the U.S. LDV market. Key components of this model include characterization of annual vehicle ownership cost, including changes in depreciation under different scenarios; utilization of elasticity estimates at an aggregate market level (i.e., elasticities that reflect changes in cost affecting the entire new vehicle market simultaneously rather than individual models); reflection of net changes in “generalized cost” rather than vehicle price only, where generalized costs refer to the change in vehicle price net of the additional benefits or costs to consumers of changes in vehicle characteristics, if any; allowing of endogenous scrappage as a function of the used-vehicle price;

and solving for equilibrium results. Our primary case assumes rational expectations in a dynamic setting, though we also explore different degrees of myopia on the part of consumers.

We then conducted a detailed review and analysis of the existing literature on the aggregate effects of changes in new-vehicle prices on new-vehicle sales, used-vehicle sales and prices, vehicle scrappage, and the factors that affect total vehicle inventory to assess the current state of knowledge in these areas. Although there have been many studies of vehicle demand, the majority have estimated elasticities at a disaggregated make/model level as opposed to the aggregate elasticities we seek for use in national-level inventory analyses. We identified only 20 relevant papers using U.S. data and published since 1995 with enough data to calculate at least one of the aggregate elasticities on which we are focused, providing a total of 25 elasticity values (five studies provided more than one estimate). There were 11 estimates of elasticity of demand for new vehicles from 11 studies, four estimates of the effects of vehicle prices on used vehicles from three studies (two estimates of the impacts of new-vehicle prices and two focused on the effects of used-vehicle prices), nine estimates of the impacts of vehicle prices on scrappage from seven studies, and one estimate of the effect of new-vehicle prices on total vehicle inventory. Based on the values identified, empirical estimates of new-vehicle demand elasticities were relatively consistent across studies, but estimates were more variable for scrappage, and very few values were available for used vehicles or total inventory. Aggregate own-price vehicle elasticities ranged from −0.37 to −1.27, though the majority of the estimates were inelastic. The three studies published within the last decade all estimated inelastic response (−0.37 to −0.78). In addition to these aggregate own-demand elasticities, two of the studies included estimated aggregate elasticities of −0.18 and −0.36 when accounting for price effects in the used-vehicle market. Available estimates of the own-price demand elasticity for used vehicles were −0.54 and −1.23, while estimates of the long-run elasticity of the used-vehicle inventory with respect to new-vehicle prices were −0.08 and −0.12. Scrappage elasticities estimated from the literature had a wide range, though the highest and lowest values were derived from simulation models, which are sensitive to assumptions. Econometrically estimated values of scrappage elasticities with respect to used-vehicle prices fell within a much narrower range of −0.36 to −0.91. There were two estimates of scrappage with respect to new-vehicle prices of −0.21 and −0.82, though the relationship between new-vehicle prices and scrappage is indirect, flowing through equilibrium effects of changes in new-vehicle prices on used-vehicle prices. The only study identified as having assessed the responsiveness of the total vehicle inventory with respect to new-vehicle prices estimated an elasticity of −0.14. Overall, relatively few studies in the literature examined the aggregate U.S.-level inventory response on which we are focused, and the majority of these studies relied on data that are from at least 20 years ago.

We then developed and parameterized an aggregate simulation model for the U.S. vehicle inventory consistent with our theoretical framework and the existing evidence available from the literature on the magnitudes of key elasticities. This model was applied to simulate both long-run steady-state and dynamic transition paths under alternative scenarios, demonstrating its ability to generate projections of vehicle inventory dynamics consistent with economic theory. To assess the effect of a policy in the long run, we examined the equilibrium where prices and scrap rates reached a new stable level (in the presence of a sustained policy change) and demand equaled supply for vehicles of each vintage between new and 30 years old. In the short and medium runs and in cases where the policy changes over time, a more complex dynamic transition occurs where prices and scrappage rates evolve over time during the simulation period. We explored response of new- and used-vehicle markets, scrappage, and size and composition of the U.S. vehicle inventory under several different sets of parameter assumptions based on economic theory and the available literature to assess the range of potential outcomes and the relative importance of individual parameters. We found that substitution to the outside good is one of the most important elasticities in determining the effect of a policy or other shocks on new-vehicle sales, yet this is perhaps the worst identified of the key elasticities estimated in the modern literature on vehicle demand that we reviewed.

Simulation of the interactions between new- and used-vehicle markets and an outside good (i.e., substitution of other forms of transportation for a personal passenger vehicle) enabled us to estimate "policy elasticities" that characterize the net equilibrium response of a change in generalized cost. Inclusion of interactions with the used-vehicle market, which is much larger in size than the new-vehicle market, dampens the policy effects of price increases on the new-vehicle market because higher purchase prices for new vehicles result in substitution toward used vehicles, raising the equilibrium price of used vehicles. Own-price elasticities for new vehicles hold other aspects of the system (such as the price of used vehicles) fixed; when used-vehicle prices also rise, there is less substitution away from purchases of new vehicles than suggested by own-price elasticities. Dynamic aspects of the system, for example, the fact that lower new-vehicle sales in the present can be expected to create shortages in the used market in the future, further contribute to the dampening of the elasticity. We found that policy elasticities are substantially smaller than the demand elasticities available from the literature, highlighting the importance of considering interactions between new- and used-vehicle markets when assessing potential effects of vehicle policy.

Typically, transportation sector regulations are both announced in advance of their date of implementation and are phased in over time. Our simulations captured key dynamics of the response to such scenarios. We observed a net increase in new-vehicle purchases between announcement of the policy and implementation as consumers anticipate higher future prices and shift new-vehicle purchases forward in time to avoid the anticipated price increases. Then, as the policy begins to be phased in and new-vehicle prices rise, new-vehicle purchases fall relative to the no-policy projection. After the policy is fully phased in, new-vehicle sales move toward their new long-run equilibrium level. For a policy that increases the generalized cost of new vehicles, new-vehicle sales will be lower than without a policy, but the long-run equilibrium change in sales will be a smaller reduction than occurs at the peak. The peak reduction in sales occurs relatively early on in policy implementation when used-vehicle supply has not yet fallen. Over time, used-vehicle supply also falls (because fewer new vehicles are entering the system); this further increases used-vehicle prices, leading some consumers to move back into the new-vehicle market as the system approaches its new steady state.

Our simulation model built on the existing literature and helped fill a gap in the available tools for analyzing aggregate impacts on vehicle markets. It offers a method for rapidly exploring potential impacts under alternative regulatory and other scenarios. Because we explicitly modeled expectations and forward-looking behavior, the model can be used to explore market reactions in anticipation of policy implementation and the impacts of phasing in policy changes over time. In addition, the model was designed to facilitate sensitivity analyses and can readily be applied to explore the range of outcomes generated using a broad range of inputs.

SECTION 1.
INTRODUCTION

Standards for vehicle greenhouse gas (GHG) emissions and fuel economy generally apply to new vehicles while existing vehicles are not required to meet the same standards. As standards become more stringent, they are expected to increase the up-front costs of new vehicles, may affect vehicle operating costs (e.g., through changes in fuel economy), and will likely affect new-vehicle sales because of their effects on new-vehicle prices and characteristics.[1] Vehicles are long-lived durable goods, and there is a wide range of model years on the road in the United States. Because of substitutability between new and used vehicles, changes that affect new-vehicle prices, sales, and operating costs are likely to also affect the market for used vehicles. Changes in the valuation of used vehicles are, in turn, likely to affect scrappage rates, where scrappage refers to the retirement of a vehicle such that it is no longer being driven. The lower a vehicle's value is, the more likely that the cost of repairing and operating that vehicle makes its economic value negative, leading the owner to scrap it. Market changes that tend to raise used-vehicle prices, on the other hand, are expected to reduce scrappage rates.

Because safety features, fuel efficiency, emissions intensity, and other vehicle characteristics vary systematically at the aggregate level by vehicle vintage, it is important to consider changes in the composition of the entire U.S. vehicle inventory. Consumer response to changes in vehicle prices and characteristics induced by regulatory policy has important implications for the total size and average age of the U.S. vehicle inventory, influencing net impacts of regulatory actions on GHG and criteria pollutant emissions, vehicle safety, and other outcomes. Thus, it is helpful to represent expected changes in used-vehicle markets and scrappage when assessing the costs and benefits of transportation, energy, environmental, or other policy affecting the transportation sector, even when the policy directly applies only to new vehicles.

The research presented in this report has three main objectives:

- Develop a theoretical framework of the U.S. passenger vehicle inventory to identify and rigorously characterize the pathways through which a policy directly affecting only new vehicles affects the entire vehicle inventory over time.

- Survey the economic literature on the aggregate effects of changes in new-vehicle prices on new-vehicle sales, used-vehicle sales and prices, vehicle scrappage, and the

[1] While similar market dynamics are expected to apply to heavy-duty vehicles, this report focuses only on the U.S. inventory of light-duty vehicles (LDVs).

factors that affect total inventory to assess the current state of knowledge in these areas.

- Develop, parameterize, and implement an aggregate simulation model of the U.S. vehicle inventory consistent with our theoretical framework and the existing evidence available from the literature on the magnitudes of key elasticities.

This analysis of the available estimates of aggregate elasticities for vehicle market responses to changes in new-vehicle prices and other factors influencing consumer behavior is intended to help provide a better understanding of the extent to which there is consensus in the literature regarding the parameters necessary to implement our theoretical framework of consumer response and resulting aggregate-level outcomes. Where the range of estimates in the literature is broad, we were likewise able to explore a wider range of inputs to the model. We conducted a detailed review and analysis of the literature and identified only 20 relevant papers using U.S. data and published since 1995 with enough data to calculate at least one of the aggregate elasticities on which we are focused, providing a total of 25 elasticity values. There were 11 estimates of elasticity of demand for new vehicles from 11 studies, four estimates of the effects of vehicle prices on used vehicles from three studies (two estimates of the impacts of new-vehicle prices and two focused on the effects of used-vehicle prices), nine estimates of the impacts of vehicle prices on scrappage from seven studies, and one estimate of the effect of new-vehicle prices on total inventory. Although there have been many additional studies of vehicle demand, the majority estimated elasticities at a disaggregated make/model level as opposed to the aggregate elasticities we seek for use in national inventory-level analyses. Those studies captured substitution between different makes and models of vehicles, but often did not report aggregate substitution between purchase of a new vehicle and an outside good of not purchasing a new vehicle, which is necessary for calculating an own-price elasticity for aggregate new-vehicle purchases. In fact, one of our findings in this study is that substitution to the outside good is one of the most important elasticities in determining the effect of a policy or other shocks on new-vehicle sales. However, it is perhaps the least studied and worst identified of the key elasticities estimated in the modern literature on vehicle demand that we reviewed.

We limited the scope of our analysis to peer-reviewed and high-quality grey literature on U.S. studies published between 1995 and the present. We considered only U.S. studies because our goal is to inform U.S. policy making, and we expected that introducing results from other countries with different vehicle choices, consumer preferences, and government policies would require additional analysis of the comparability of elasticities estimated under those differing conditions. In addition, consumers' preferences can change over time. Focusing on more recent studies is intended to make our analysis more relevant to current policy making. Within the papers identified that met our criteria for inclusion, we focused on the authors' preferred model for each category of elasticity available within their study. Based on the values identified, empirical estimates of new-vehicle demand elasticities were relatively consistent across studies, but estimates were more variable for scrappage, and very few values were available for used vehicles or total vehicle inventory.

Because our review of the existing literature revealed few studies that provided estimates of any of the parameters necessary for empirical application of our theoretical model, let alone a full set of parameters consistent with our theoretical specification, we developed a new dynamic simulation model of the U.S. passenger vehicle inventory. Existing models that address the used market are scarce, and many either ignore the dynamics or have difficult-to-interpret reduced forms and thus can produce inconsistent results. The simulation of the used-vehicle market in Jacobsen and van Benthem (2015) is most similar to the model structure proposed here.[2] In that model, price expectations are myopic, however, so it presents only one view of the aggregate implications. Welfare analysis is also prevented or made very difficult when expectations are myopic (because the nature and degree of mistakes in expectations are not well defined).

Our new model is consistent with economic theory under rational expectations and reflects substitution between vehicles of different vintages, ranging from new to 30 years old, and effects on scrappage rates in response to changes in the market for new vehicles. Key contributions of this study include assessment of the available literature estimating the parameters necessary for parameterization of an aggregate model of U.S. vehicle markets, development of a dynamic aggregate model consistent with economic theory, fuller treatment of expectations in the used-vehicle market, comparison of the net responsiveness of new- and used-vehicle sales and total vehicle inventory within this model with the elasticities available from the literature, and analysis of the dynamics of U.S. vehicle markets and inventory response under alternative scenarios. The lifespan of LDVs is long enough that some of the most important policy impacts on inventory size and age composition are likely to occur along the transition path (perhaps over a span of decades). We modeled both the long-run outcomes and the time path taken to reach those outcomes.

[2] As noted by a reviewer, Adda and Cooper (2000) and Schiraldi (2011) also presented dynamic models of the new and used vehicle markets. Adda and Cooper (2000) used annual time-series data for the United States and France to estimate vector autoregression and discrete choice models. They did not report price elasticities and focused largely on the dynamic relationship between shocks to income, price, and taste. Schiraldi (2011) focused on identifying transactions costs and applied their model to evaluate the impacts of scrappage subsidies on the Italian vehicle market in 1997 and 1998. We do not include these results in Section 5 because our focus is on U.S. markets.

The following section provides background information on the evolution of the U.S. vehicle inventory over time and key macroeconomic drivers of changes in inventory size and composition. This is followed by presentation of our theoretical framework for characterizing the U.S. vehicle inventory at an aggregate level in Section 3. Methods employed for our literature review and synthesis are described in Section 4. Section 5 presents descriptive statistics and analysis of the results of our literature review. In Section 6, we present the methodology used for empirical implementation of our theoretical framework within a long-run steady-state simulation model of the U.S. vehicle inventory. Section 7 presents results from the long-run steady-state model. We then present dynamic transition path modeling in Section 8 and results from selected dynamic scenarios in Section 9. Finally, in Section 10 we conclude by reflecting on the available evidence from the existing literature and the contributions of our study and discuss model applicability, potential linkages to other models, and limitations and caveats of this approach.

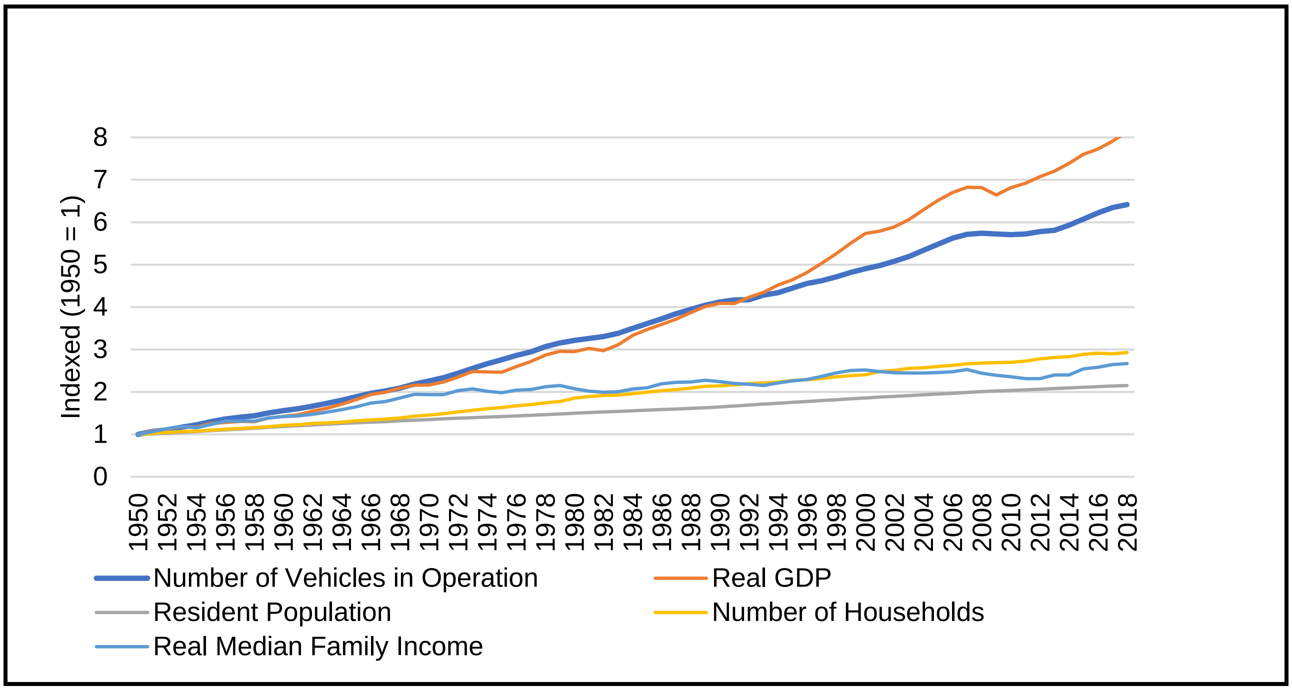
SECTION 2.
CHARACTERIZATION OF THE U.S. PASSENGER VEHICLE INVENTORY

This section provides a brief summary of historical changes in the U.S. vehicle inventory and selected variables that may be important contributors to the evolution of the passenger vehicle inventory over time.

2.1 Growth of the U.S. Passenger Vehicle Inventory and Contributing Factors

The U.S. LDV inventory grew significantly from 1950 to 2017. In 1950, there were approximately 43.5 million LDVs in operation. By 2017, there were over 276.1 million. This represents a 535% increase in the number of LDVs in operation. Figure 2-1 illustrates the change in the size of the LDV inventory alongside variables expected to influence LDV inventory, including gross domestic product (GDP), median household income, population, and the number of households.

Figure 2-1. Vehicle Growth, Population, and Macroeconomic Indicators Comparison, 1950–2018

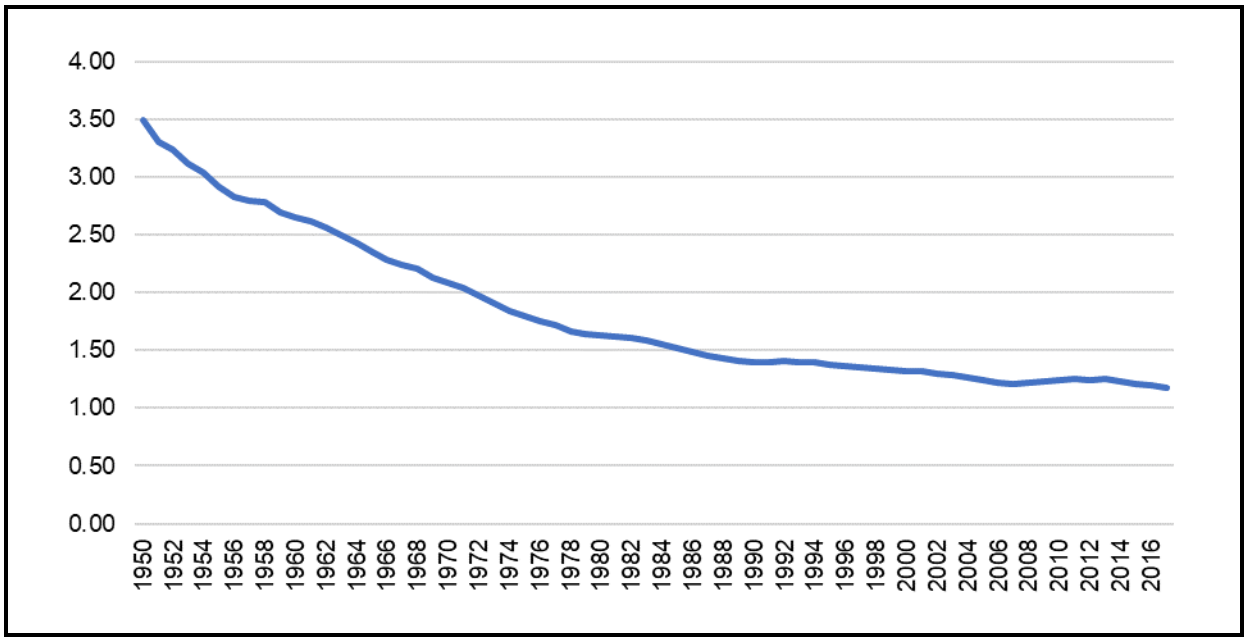


Sources: Oak Ridge National Laboratories (ORNL) (2021a) and Federal Reserve Economic Data (FRED) (2020a, 2020b)

The growth in GDP appears to be a very important driver of the size of the LDV inventory. GDP and the number of vehicles in operation follow very similar trends from 1950–1990. GDP growth has outpaced growth in the size of the LDV inventory since 1990, but they have continued following similar trajectories. Strong GDP growth is indicative of rising income and strong market confidence, which are likely key driving factors behind continued growth in the size of the vehicle inventory (Sivak, 2013).

As the U.S. population has grown, the demand for additional vehicles has increased. Population growth cannot entirely account for the growth in the number of passenger vehicles, however. The growth in LDVs has greatly outpaced the growth in the U.S. population, as shown in Figure 2-2. In 1950, there were approximately 3.5 people per vehicle. By 2017, that number had shrunk to 1.18. This is also evident when examining the number of vehicles per household. In 1950, the average household owned a single vehicle. In 2017, the average household owned 2.19 vehicles, even as the average number of people per household declined. The ratios of both vehicles to people and vehicles to households have strongly increased over time. It appears that the U.S. passenger vehicle inventory may be approaching market saturation as the change in the number of people per vehicle has flattened in recent decades.

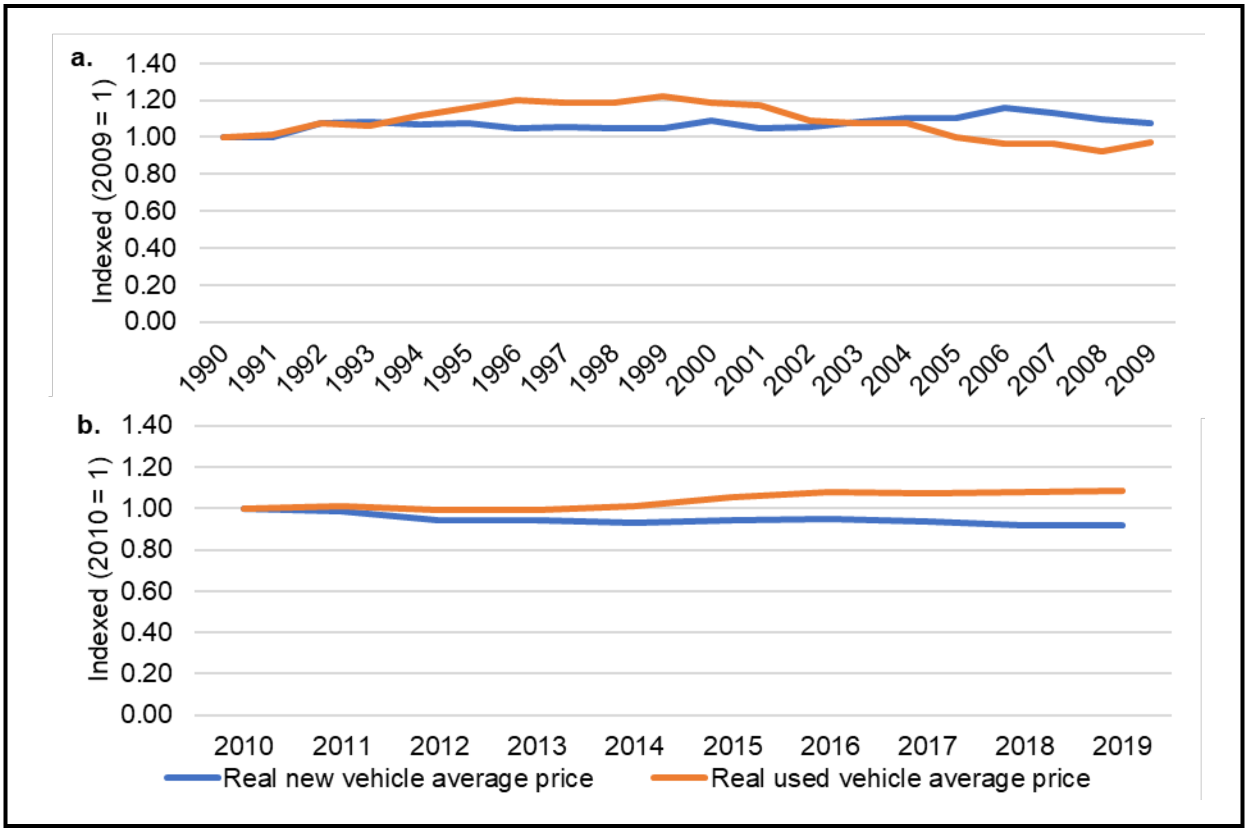
Figure 2-2. Number of People per Vehicle, 1950–2017



Source: Authors' calculations using data from ORNL (2021a) and FRED (2020a, 2020b).

Real median family income has remained relatively flat over the past few decades, suggesting that purchasing power has not drastically increased over this time. While the data for new- and used-vehicle prices are not available for this full time period, they are available for more recent years. The Bureau of Transportation Statistics (BTS) used different sources for new and used average vehicle prices for the time period 1990–2009 and the time period 2010–2019, which results in a large shift in the average price level between these two periods. Thus, we report these two periods as indexes with two separate base years rather than in levels to make them more comparable (see Figure 2-3). Real vehicle prices are relatively flat over this time period, though used-vehicle prices have experienced greater percentage changes over time than for new vehicles. In general, vehicle prices rose more rapidly for used vehicles than new throughout most of the 1990s before trending downward through the 2000s until 2008, even as new-vehicle prices continued to rise. This pattern has reversed again since the financial crisis in 2008, with used-vehicle prices trending upward as new-vehicle prices have fallen.

Figure 2-3. Index of Real Average New- and Used-Vehicle Prices, 1990–2019



Source: BTS (2020)

Note: BTS switched data sources between 1990-2009 (2-3a) and 2010-2019 (2-3b), resulting in a large upward shift in the average price of both new and used vehicles between the two periods. Thus, we are presenting these data as indices with separate base periods to make them more comparable.

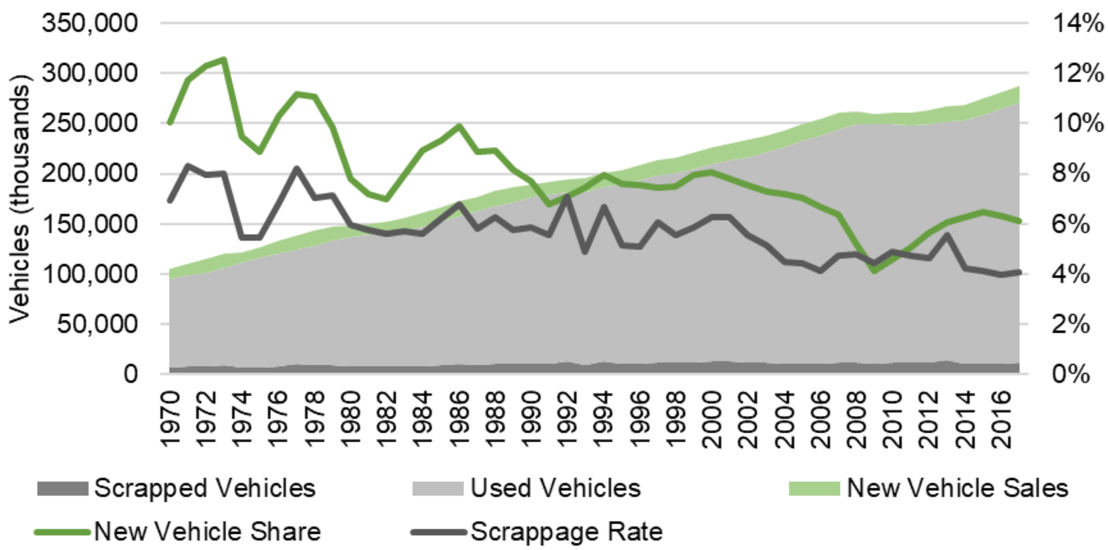
2.2 Composition of the U.S. Passenger Vehicle Inventory

The size of the U.S. LDV inventory has grown over time, driven by new-vehicle sales exceeding scrappage. This relationship is represented using the following formula:

$$Inventory\ (Current\ Year) = Inventory\ (Previous\ Year) + New\text{-}vehicle\ sales - Scrapped\ Vehicles$$

Figure 2-4 illustrates changes in the inventory over time with the number of new vehicles, used vehicles, and scrapped vehicles, as well as changes in the share of new-vehicle sales and the scrappage rate over time.

Figure 2-4. Composition of the U.S. Passenger Vehicle Inventory, New-Vehicle Share, and Scrappage Rate, 1970–2017

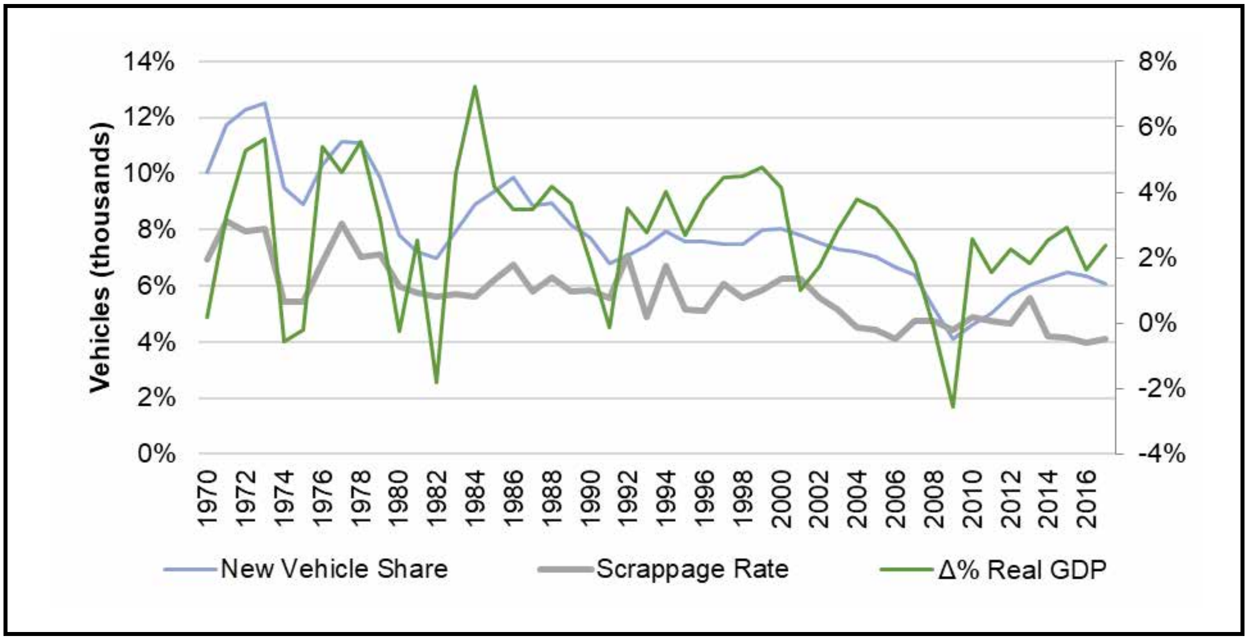


Sources: BTS (2017), BTS (2020), and ORNL (2021a)

On average, for the period 1970–2017, new vehicles made up 7.9% of passenger vehicles. In the same period, 5.7% of passenger vehicles were scrapped each year. There is some fluctuation, however, with the share of new vehicles peaking in 1973 at 12.5% and dropping as low as 4.1% in 2009. The most recent downturns in new-vehicle share and scrappage rates occurred in or around 1990, 2001, and 2008–2009. It should be noted that these time periods correspond to the early 1990s recession, the early 2000s recession, and the Great Recession. As market confidence wanes and people's financial situations worsen, they often opt to continue driving their used vehicles longer and delay the purchase of a new vehicle. This behavior is characteristic for durable goods such as vehicles. For example, FRED (2018) found that expenditures on motor vehicles and parts dropped by as much as 24% during recessions.

While year-to-year fluctuations in the share of new vehicles and the scrappage rate tend to move with changes in real GDP, there has been a downward trend in the share of new vehicles in the passenger vehicle inventory and the scrappage rate since 1970 despite overall economic growth (see Figure 2-4). This trend is likely due at least in part to increased vehicle reliability over time. Consumers can continue driving their vehicles for longer, thus reducing the need to purchase a new vehicle. This fact is reflected in the average age of vehicles. According to data from ORNL (2021b), in 1970, the average passenger vehicle was 5.6 years old and the average light truck was 7.3 years old. By 2018, the average age of a passenger vehicle more than doubled to 11.9 years. The average age of a light truck increased by 60% to 11.7 years.

Figure 2-5. New-Vehicle Share and Scrappage Rate Relative to Percentage Change in Real GDP, 1970–2017



Sources: BTS (2017), BTS (2020), and FRED (2020)

SECTION 3.
THEORETICAL BACKGROUND

U.S. policy directed at the pollution emissions or fuel consumption of LDVs has tended to concentrate on new vehicles, requiring improvements in technology or changes in attributes to reduce externalities. However, there are substantial interactions between new- and used-vehicle markets that have potentially important implications for the net impacts of such policies on the U.S. vehicle inventory. This section qualitatively discusses important considerations for developing a framework to adequately identify and rigorously categorize the channels through which a policy directed only at new vehicles will eventually make its way through the whole vehicle inventory. Empirical implementation of this framework is presented in Section 6.

3.1 Characterizing Vehicle Markets

As with other goods and services, equilibrium prices and quantities in LDV markets are determined by supply and demand. However, several characteristics of vehicles make representation of this important market relatively complex:

- Vehicles are quite heterogeneous, with wide variation in model type, comfort, size, handling, horsepower, handling, fuel economy, and other characteristics. Consumers have substantial willingness-to-pay values for improved quality of many characteristics (Greene et al., 2018a, 2018b).

- Vehicles are long-lived durable goods such that they are available in many different vintages simultaneously. There is substantial substitutability between similar vehicles of different vintages, though presumably declining substitutability among vehicles as the difference in vintage increases.

- When vehicles need repairs, owners evaluate whether it is preferable to repair the vehicle or to scrap it and shift to an alternative means of transportation (e.g., new vehicle, used vehicle, or other transportation).

- Production of vehicles is very capital intensive with a multiyear planning horizon for vehicle manufacturers to introduce new models or major changes to existing models. Nonetheless, in the long run manufacturers build or modify plants and new firms enter, meaning that the long-run supply of newly manufactured vehicles is likely to be relatively elastic.[3] The supply of used vehicles, however, is expected to be much less elastic because scrappage is the only channel of adjustment.

- Certain vehicle characteristics vary systematically with vintage, including safety, fuel economy, and emissions. Thus, scenarios that alter the total vehicle inventory or the distribution of vintages within the inventory can result in substantial national benefits

[3] Blonigen et al. (2017) explored long-run competition and entry of vehicle models via redesigns.

and costs associated with changes in safety, energy markets, and environmental outcomes.

Because of the extensive substitution between new and used vehicles and between vintages within the used-vehicle market, it is vital to jointly model the new and used markets when assessing alternative scenarios affecting the vehicle market. In this study, we focus on aggregate-level characterization of vehicle markets, capturing substitution between vintages and scrappage decisions while abstracting from other heterogeneity within the sector to develop a theoretically consistent model of the aggregate U.S. national vehicle market.

3.1.1 Utility and Demand

Household utility functions determine the choice of vehicles (e.g., number, age, type) and other goods and services consumed by households for a given set of prices. When the utility model is of an individual household, the choice may be modeled as discrete (i.e., new vehicle, used vehicle, or no vehicle). When the function represents all households together (more typical in the scrappage literature, and the approach we take here), it represents the sum of many individual, discrete choices that can be approximated as a continuous function. Empirical estimates of a utility function are often summarized using a matrix of demand elasticities.[4] Three caveats, discussed below, about many of the vehicle demand estimations in the literature deserve emphasis in this context.

3.1.1.1 Ownership Cost and Durability

When allowing for the possibility of reselling used vehicles, the distinction between the current market price of a vehicle and the net cost of ownership per unit of time becomes important and is not always made clear in the literature. One of the largest costs of ownership, particularly for newer vehicles, is depreciation. Other things being equal, if the price of a new LDV remained unchanged but the price of used vehicles rose, new vehicle shoppers would view that increase in the price of used vehicles as evidence that a vehicle "holds its value well," and would demand more new vehicles because the cost of ownership has declined (i.e., when they sell or trade in the vehicle in the future, the residual value will be higher, thus lowering the depreciation their vehicle will experience).

The fundamental difficulty with demand derivatives in this setting comes from the durable nature of LDVs. The canonical theory of utility and demand assumes that prices correspond to goods that are consumed within the scope of the utility function. Here, the

[4] Elasticities are widely used in economics and are measures of how responsive one variable is to changes in another. Demand elasticities refer to the percentage change in the quantity demanded of a product for a given percentage change in the price of that product, all else equal.

purchase price of a vehicle not only includes the cost of enjoying it in the current time period (over which utility is being defined), but it also includes a whole series of future ownership costs (perhaps not even borne by the same individual); an increase in purchase price indicates that somewhere in a vehicle's future the ownership cost has gone up, but it does not isolate when in time that ownership cost has increased.

In the literature estimating new-vehicle demand systems (e.g., Berry, Levinson, and Pakes [BLP] [1995]), the distinction between purchase price and net ownership costs is often not discussed. That paper, for example, considers only new vehicles and provides estimates of the responsiveness of the quantity of new vehicles purchased to the price of new vehicles. In a setting where we want to simultaneously consider decisions about new and used vehicles it is important to convert new-vehicle price derivatives into ownership cost derivatives. The conversion requires an estimate of the fraction of the increase in new-vehicle price that is borne by the new vehicle owner, as compared with the fraction they can pass through to future users of the vehicle. Consider the effect of a $5,000 increase in the purchase price of a new vehicle on a buyer who plans to use that vehicle for the first decade of its life and then sell it. If the buyer believes they will pay almost all that $5,000 themselves (i.e., the residual value of 10-year-old vehicles in 10 years from now will remain unchanged from what it was prior to the price increase), then there could be a sharp drop in demand for the new vehicle. On the other hand, if the purchase price rises by $5,000 but the residual value of 10-year-old vehicles in 10 years is expected to rise by $3,000, the demand response of the same new vehicle buyer facing the same purchase price increment becomes much smaller. Data on new and used LDV prices (implying a sequence of values for depreciation and ownership cost) can be used to construct an estimate of the proportion of changes in new-vehicle purchase price new-vehicle buyers will be able to pass through to future users versus the fraction they will bear themselves.

3.1.1.2 Aggregation of Elasticities

For the purposes of many questions in the vehicle literature (e.g., a vehicle manufacturer's choices about markups), elasticities at a micro level are the relevant unit. A company can consider raising or lowering the price of one individual model, or even one individual trim, by itself. In contrast, questions relevant to policy making are typically at a more aggregate level: suppose a regulation imposes a cost (either an engineering cost or a shadow cost) on the entire new vehicle market at once. How will consumers respond to this? The transformation needed to answer this involves adding up the whole "block" of own- and cross-price demand derivatives for new vehicles.[5] Intuitively, if most of the substitution reflected in a demand derivative for a new vehicle is just substitution to other new vehicles (as opposed to used vehicles or public transit), then the aggregate demand derivative may be very small even when the demand derivative for individual models or trims is quite large.

Much of the literature presents only "average" elasticities, that is, the average own-price elasticity among individual models of new vehicles. Average elasticities tend to be larger and may be substantially larger in magnitude than the *aggregate* own-price elasticity. In Section 5, we focus on aggregate rather than average elasticities. Sometimes these are presented directly in the papers reviewed, and in other cases we can compute them if sufficient data are provided in the paper. Many papers that focus on estimating demand at the level of individual models are not necessarily structured in such a way as to enable estimation of these aggregate elasticities, however, because they typically do not include the possibility of substitution to an outside good.

3.1.1.3 Simultaneous Changes in Indirect Utility

The derivatives of demand here reflect a world where (at least from the consumer's perspective) only the price of new vehicles has increased, with no change in perceived vehicle quality. This concept is only sufficient in specialized examples where the benefits from a regulation are fully diffuse (so an imperceptibly small amount of the benefit goes back to an individual vehicle consumer) and where the technology used to provide this benefit is invisible. Pure examples like this are hard to find in the space of automobiles, but certain tailpipe regulations on smog-forming pollutants may come close: suppose an extra $100 is spent using a more expensive metal in a catalytic converter. If this causes it to work better at reducing smog but is imperceptible to the consumer (i.e., no changes in maintenance, longevity, power, etc.), then measuring the price increase by itself is enough to understand the effect of the policy on demand for new and used vehicles.

More often, however, the price increase creates environmental benefits that are diffuse but also changes the way the vehicle works (either for the better or worse) such that the consumer sees a simultaneous change in price *and* something else about the vehicle. Some tailpipe requirements on smog-forming pollutants may reduce power, for example, or create fear of increased "check-engine" faults as the systems grow more complex. This creates a challenge because the degree to which these things bother consumers is often unknown. The same $100

[5] In much of the new-vehicle literature, the derivative presented is with respect to price, implicitly suggesting that the rental or depreciation price entering utility is a constant fraction of the new-vehicle price. For the literature on used vehicles, the derivative will tend to be with respect to depreciation or rental price directly. The aggregation problem applies regardless.

price increase, when it comes together with some power loss or maintenance fear, might look more like a much larger price increase in terms of how the consumer reacts. Although it is theoretically possible to estimate the effects of changes in quality on consumer valuation of vehicles, there is relatively limited literature for many vehicle attributes and considerable variability in the available estimates. Greene et al. (2018) summarized the literature on consumer willingness to pay for vehicle attributes.

Fuel-economy regulations create an even more challenging environment in this sense. By their very nature, the benefits of improved fuel economy are shared. Part of the benefits from reduced gasoline use (e.g., improved health and environmental conditions resulting from lower emissions) are diffuse and go to society, while another part (the money savings at the pump) goes directly to the vehicle owner. If we do not know how consumers view these savings, we cannot determine the net change in indirect utility. For example, suppose fuel-economy policy raises the new-vehicle price by $100 (and power and all other attributes are fixed), while discounted future fuel expenditures on that vehicle fall by $150. A consumer might mistakenly think there will only be $100 in gasoline savings and would see this policy as a net zero on indirect utility. Their demand for new vehicles would not change at all. Another consumer may think there will only be $60 in fuel savings. They would react to this policy as if it were a $40 *increase* in cost, reducing their demand by some, but not by as much as they would for a $100 loss in indirect utility (see Greene et al. [2018] and Greene, Evans, and Hiestand [2013] for discussion of consumers' willingness to pay for fuel economy). In addition to differences in perceptions of what their discounted savings over time may be for a given driving pattern, there is also heterogeneity across consumers in the distance they anticipate driving. Consumers who anticipate driving a greater distance per unit time are expected to place a higher value on fuel economy than those who drive less.

We will refer to the combined change in perceived cost at the time of purchase as a "generalized cost." Consumers will be assumed to respond to a $100 increase in generalized cost the same way they would respond to a $100 price increase when the attributes of the vehicle remain unchanged. Valuation of changes in vehicle attributes may vary widely across individual consumers. In our aggregate model characterization, the value of the generalized cost used represents the net change in vehicle cost perceived by the average consumer.[6]

Making use of a demand system in this setting requires three sets of estimates: i) the demand elasticity as above, ii) the price increase associated with the regulation, and iii) the perceived utility loss (or gain) associated with the engineering change. We assumed that combining (ii) and (iii) into generalized cost and then multiplying by (i) leads to the percentage change in quantity demanded.

3.1.2 Supply and Scrappage

The supply of newly manufactured vehicles is likely to be fairly elastic, especially in the long run when companies can expand and new entrants can appear. When supply of a product is elastic, and no used versions are present, a demand system alone (like the one described above) is enough to accurately predict what will happen when there is a cost increase due to regulation. The projection for a new equilibrium quantity can be read directly from the cost increase and the estimated demand elasticity. However, the presence of a used market interacts with the equilibrium system and the new-vehicle demand elasticity is no longer sufficient to measure the effect of a policy.

The aggregate supply of used vehicles, in contrast, is far less elastic than that of new models. When a particular used model's price rises, more of that model become available in total (e.g., because used-vehicle owners are more likely to trade a valuable used vehicle in than sell it for scrap metal, and because vehicle dealers, insurance companies, and mechanics decide to repair and sell a greater fraction of the stream of used vehicles they receive). However, this effect remains limited by the overall number of vehicles of a certain vintage and model that are available in the system. Because the elasticity of supply for used models appears to be intermediate, neither very close to zero nor very close to infinity, the equilibrium outcome for these vehicles depends importantly on *both* the elasticity of demand and supply (where used-vehicle supply is inversely related to scrappage).

The most straightforward scrappage function for used vehicles (which can be inverted to determine used-vehicle supply) can be derived from an underlying, fixed distribution of repair cost shocks (e.g., costs from mechanical failures and accidents). A simple model of scrappage

[6] As pointed out by a reviewer, one caveat to using generalized cost is that a regulation that changes the attributes of vehicles may change the substitutability between new and used vehicles. In that case, the relative allocation of the change in generalized cost between changes in vehicle price and attributes may be something to consider. This effect may become more important in the future if applying the model to explore the transition to electric or autonomous vehicles, where major differences in attributes could lead to large changes in substitution between new and used vehicles.

states that scrap occurs when these shocks exceed the value of a vehicle.[7] In contrast to the issue identified for demand elasticities whereby demand elasticities vary by level of aggregation (i.e., elasticities increase with the level of disaggregation because some or even all of the substitution may be taking place between the disaggregated vehicle categories), we assumed that vehicle scrappage depends only on own price of vehicles.[8]

Empirical estimates will typically be presented as a derivative of the density or elasticity of this function, rather than of the density of underlying shocks that determines the function. This is analogous to utility functions, where estimates are typically presented as elasticities or derivatives rather than as direct utility function parameters.

3.1.3 Equilibrium and Estimation

Evaluating equilibrium effects is the end goal of a policy analysis, but in the context of estimating the two underlying functions above (demand elasticities and scrappage elasticities) the presence of equilibrium effects in observational data leads to biased estimates.[9] A biased estimate of the scrap function, for example, might partly reflect the desired underlying scrap-price relationship, but also partly reflect an equilibrium process in the real-world evolution of prices and vehicle stocks.

Expanding on the example of a scrap function, notice that in the framework above it is only a used vehicle's own value (and the comparison of that value to a repair cost shock) that determines scrappage. The derivative of the scrappage function with respect to a change in the price of new vehicles is zero. However, even when there is no direct channel for new-vehicle prices, they will still have an important *equilibrium* impact on scrappage: increases in new-vehicle prices tend to increase used-vehicle values, so we might observe that new-vehicle prices in fact create quite large changes in scrappage. Some of the equilibrium increase in used-vehicle values could be immediate (via changes in expectations or substitution in the demand system),

[7] The presence of transactions costs could lead to a more complicated scrappage function that directly involves the prices of other, perhaps even new, vehicles. Jacobsen and van Benthem (2015) present a range of arguments why the prices of other vehicles are unlikely to be important direct determinants of scrap.

[8] As pointed out by a reviewer, the vehicle scrappage decision should theoretically also depend on the prices of other vehicles to the extent that parts needed for certain repairs are interchangeable and supply curves for these parts slope upwards. This is undoubtably true in the short term and when sourcing repair parts from scrapped used vehicles, though manufacturers can respond to rising prices by increasing production of these parts, which would mitigate price increases, or even reverse them to the extent there are economies of scale. In addition, our aggregate model represents an entire vehicle vintage as a single representative vehicle. Thus, we assumed that the scrappage decision depends only on the own price of that aggregate vehicle.

[9] Equilibrium changes can act as omitted variables (to the extent that not all prices and quantities are included in the same regression) or as conduits for other omissions (e.g., taste shocks that affect more than one vintage of a vehicle at once).

but there will also be changes over time as the currently new portion of the inventory ages and creates shortages in the used market. The resulting equilibrium increase in used-vehicle value is what enters the scrap function and determines the scrap rate.

To provide a concrete empirical example, consider running a fixed-effects regression of scrap rates on new-vehicle prices. We want to learn how much each $1 of increase in new-vehicle prices lowers the scrap rates of used vehicles. An empirical estimate of this relationship is a reduced form, in that it reflects the chain of effects that runs first from new prices to used prices and then through a scrap function and into scrap rates.[10] Any unobserved shock that affects markets for new and used together will confound this regression. As an example, suppose many fixed effects (e.g., time, vehicle class) are included so that only cross-model variation in prices and scrap rates remains. Even in this setting the estimates will be confounded: unobserved shocks that make a single model more popular will both allow the manufacturer to raise the price of new versions *and* provide a boost in demand for used versions. Scrap rates may appear to fall dramatically when new prices rise, but this comes both from the effect we want to measure (which is an indirect one, coming through the chain of price effects from new to used and then on to scrappage) and the direct effect from the model-level increase in utility. There is also a possibility for reverse causality: a downward shock to the scrap rate will create more competition for new versions of a vehicle (because there are now more used ones remaining in the market), leading manufacturers to lower prices. Estimating the reduced form successfully would require good quasi-experimental variation in new-vehicle prices, but the likely confounders and long time series required have meant that the literature has been unable to find many suitable settings. Even with a setting providing good variation in new-vehicle prices, it will remain challenging to identify the appropriate elasticity given the importance of cross-price elasticities with used vehicle prices, which are reflected in equilibrium.

In contrast, the goal of the underlying parameters approach outlined here is to separate the two steps between a shock to new-vehicle prices and effects on quantities in the used market. Credible variation exists to identify demand derivatives (e.g., the approach in BLP and others), and quasi-experimental variation in used-vehicle prices is also available to identify scrap elasticities. Separating these two links in the chain makes it easier to demonstrate economic consistency within each link and, therefore, in the overall estimate.

[10] If the variation in the data that creates the change in new-vehicle prices is also connected to other aspects of the vehicle market or macroeconomy, notice that these other effects will also be wrapped into the observed values of scrappage. A change in policy would likely create a different outcome. The underlying scrap function, on the other hand, stays the same regardless of the source of change in used-vehicle value.

3.2 Considerations for Framework Development

3.2.1 Key Questions

A policy that increases new-vehicle prices (or more generally that decreases indirect utility associated with new vehicles[11]) will have a cascade of effects on vehicle quantities throughout all vintages within the inventory. First, and perhaps most directly, the higher prices will mean that fewer new vehicles are purchased, with the magnitude of the reduction partially determined by the aggregate own-price elasticity of demand. Moving forward in time, reductions in new-vehicle sales will start to produce shortages in the used-vehicle market (e.g., reductions in sales of new 2020 model-year vehicles mean that there will be fewer used 2020 vehicles available in all future years). The reduced availability will lead to a higher equilibrium price of used vehicles than would have been observed in the absence of the policy. Another effect (present in both the short and long runs) comes via cross-price elasticities of demand for new vehicles. If the increase in price of new vehicles causes some consumers to purchase in the used market instead (i.e., a substitution effect), this flow of former new vehicle buyers into the used market will also tend to drive used-vehicle prices up.

Through both of these channels, used-vehicle prices will increase as a result of the new vehicle policy. Higher used LDV prices in turn have two key effects. First, higher prices will force some used-vehicle buyers out of the market—to an "outside option" like public transportation or carpooling. Second, higher used-vehicle prices will make used vehicles worth maintaining for longer, reducing scrappage and partially offsetting some of the shortages that have appeared in the used market.

How do the effects on the composition of the vehicle inventory relate to the initial policy goals? Longer vehicle lifetimes mean larger used-vehicle inventories and older average vintages, tending to erode environmental improvements that might have been expected in a world where inventory turnover, and thus the distribution of the vehicle inventory across vintages, remains at baseline levels. How large this effect is empirically depends on all the parameters that control the cascade of effects described above. For example, how easily do LDV consumers substitute from new vehicles to used vehicles or from personal vehicles generally to public transit or carpooling?

[11] We use the term "price increase" throughout, but the concepts apply to any reduction in indirect utility from a new vehicle purchase. Indirect utility holds income fixed and reflects the maximum utility a consumer can attain. A vehicle price increase, therefore, reduces indirect utility because it reduces the amount of money left over to buy other goods. A reduction in weight and horsepower (holding vehicle price constant) also reduces indirect utility: even though the budget for and consumption of other goods is unaffected, total utility declines to the extent the vehicle produces less utility when driven. Improvements in other attributes (like fuel economy), on the other hand, can partially or fully offset price increases in the indirect utility measure; we are interested in the effect of a price increase net of utility enhancements.

For the group of consumers that substitutes from new to used, how much does this substitution drive up equilibrium used-vehicle prices? When buyers substitute between new vehicles and used vehicles, which vintages are they substituting toward (e.g., likely relatively recent model used vehicles) and how does this affect the distribution of price changes across vehicles of different vintages? How does substitution between used vehicles of different vintages work out in equilibrium?[12] Finally, to what extent does the increase in used-vehicle values make repairs more worthwhile, thereby reducing scrappage and increasing the size of the used inventory?

The chain of effects above can be illustrated in a simplified supply and demand illustration where there are only two types of vehicles, "new" and "used." The left panel of Figure 3-1 displays the new-vehicle market. The original impulse is an upward movement in the (horizontal for convenience) supply curve in the new market: new-vehicle supply moves from S_n to S_n' and produces a corresponding increase in price. If the demand curve for new vehicles remained at the baseline, D_n, equilibrium quantity would simply fall from point A to point B. The amount of the decline in quantity from point A to B is given by the demand elasticity for new vehicles. However, in equilibrium, prices in the used market will also rise. Because new and used cars are substitutable, this will cause the demand curve for new cars to shift to the right, to a line like the one labeled D_n'. The amount the demand curve shifts to the right is determined by the elasticity of substitution between new and used vehicles. The final change in new car quantity is then given by a move from point A to point C. This decline in quantity is what we call the *policy elasticity* of new-vehicle sales in the following discussion.

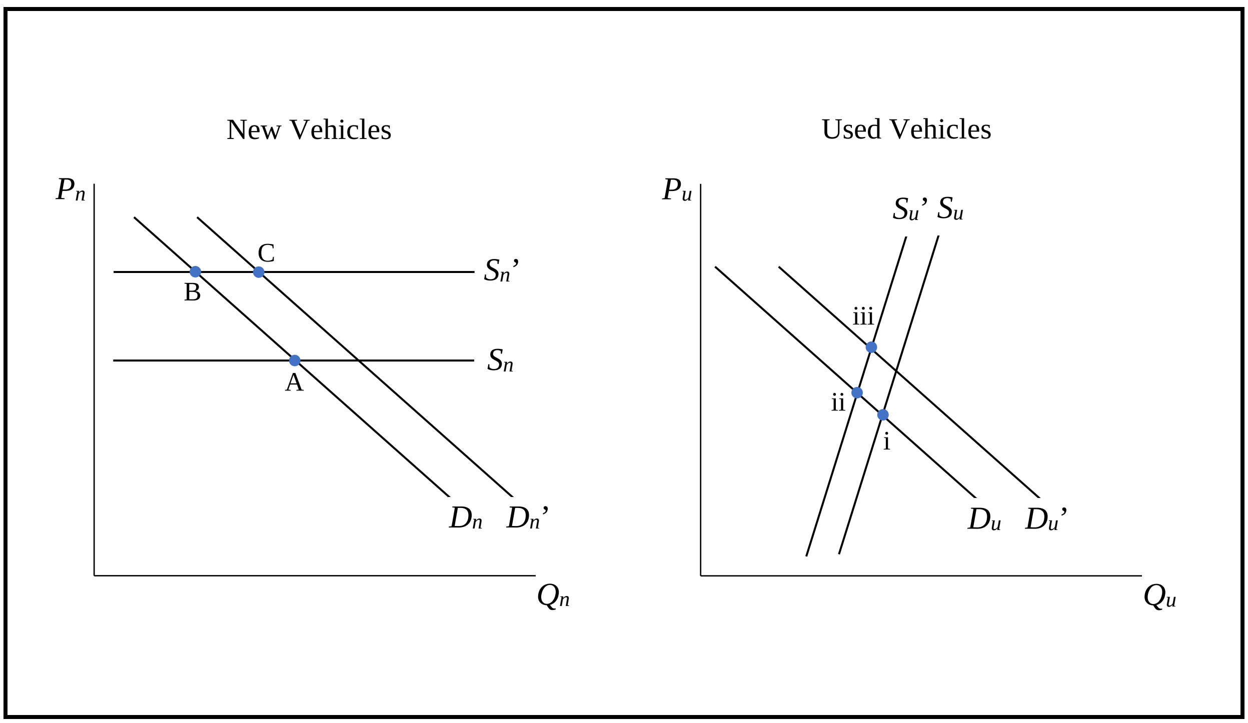
Why do prices rise in the used market? As explained above, there are two main reasons. The first is the scarcity of new cars feeding into the used market. When quantity drops from A to C in the new market, the supply of used vehicles shifts to the left by a similar amount (the long-run maximum number of used vehicles, if all accidents and breakdowns are fully repaired, is determined by the number of new vehicles coming in). This is shown in the right-hand panel of Figure 3-1 with the shift from S_u to S_u'. The slope of the S_u curves is determined by the scrappage elasticity. If scrappage responds a lot to vehicle value, then the curves are flatter, or in the extreme case where scrappage is completely predetermined, these curves would instead be vertical. The inward shift in the used-vehicle supply curve increases used-vehicle prices (and reduces quantities) from point i to point ii in the figure. The other force influencing the used market is substitution. The increase in new-vehicle prices in the left panel increases demand for

[12] In the default assumptions within our simulation model, we assumed higher substitutability between vehicles that are closer in age. We believe this assumption is reasonable, but there is relatively little empirical data on how to parameterize these substitution patterns, so we examined a wide range of other possibilities, detailed in Appendix C.

used substitutes. This substitution appears as a shift out in demand for used vehicles, shown in the movement from D_u to D_u'. As before, the size of the shift out in demand is determined by cross-price elasticities between new and used vehicles. The final equilibrium outcome in the used market is then a shift from point i to point iii. Note that the price of used vehicles always increases (both forces operate in the same direction), but the direction of the quantity change is ambiguous. It depends on the relative slopes of D_u (determined by the price elasticity of demand for used vehicles) and S_u (determined by the scrappage elasticity).

In the model in Section 6, we parameterized these slopes and allowed for many interactions among ages, considering 30 overlapping vintages, so that we can calculate equilibrium results throughout the age profile. It may be interesting in future work to see if an analytically tractable model with just two ages is feasible in closed form; if so, it could help to further the intuition for patterns in our quantitative model output below.

Figure 3-1. Diagram of Outcomes in New and Used Markets



3.2.2 Overview of Approaches

Two broad empirical approaches are available to understand effects over time in the new and used portions of the inventory. One approach is a "quasi-experiment": the analyst would need to find a shock that changes all new-vehicle prices without also directly affecting used vehicles or other features of the economy that influence vehicle demand. The short-run effects from a quasi-experimental increase in all new-vehicle prices could then be studied by examining the response the shock produces in new and used markets. However, because transportation is such a fundamental component of the economy, finding a good quasi-experiment has proven difficult: most factors that increase new-vehicle price have some other connection to the vehicle market, so the experiment becomes confounded. It is even more challenging to study long-run equilibrium effects on the used market using a quasi-experiment because the quasi-experimental increase in new-vehicle prices would need to be very long-lived, lasting at least for the typical lifetime of a vehicle, to study features of the used market as it transitions to a new steady-state equilibrium.

A core reason the economics literature has not been able to find good quasi-experimental variation may be the strong connection between automobile sales (both new and used) and macroeconomic variables like employment and wages. A quasi-experiment that changes the price of just one new vehicle model might not have enough connection to the macroeconomy to confound the estimate, but for the aggregate impacts relevant here one needs a shock that changes the prices of all new vehicles at once. For example, changes in the prices of inputs to making vehicles (labor, metals, energy, and so forth), of course, do change new-vehicle prices, but the effect coming from price alone cannot be disentangled from other effects these changes would have on vehicle demand. Changes in the overall tax regime for new vehicles may be related to macroeconomic fluctuations and so forth. Additionally, factors that affect production of new vehicles are likely to affect components produced for use in repairs, and so confound elasticities between the new and used markets.

Finally, another difficulty with a quasi-experimental approach is that the price shock needs to be independent of vehicle attributes valued by consumers. Otherwise, it becomes difficult to separate out the quality-adjusted price shock. For instance, many historical price shocks that directly affect new vehicles are associated with regulations that mandate increased safety (e.g., seat belts, airbags) or fuel economy, either of which provide benefits to consumers that need to be assessed to evaluate the net change in indirect utility.

A second empirical approach is to estimate a set of underlying parameters that control the system and then use those parameters to simulate how vehicle markets evolve over time when there is an external increase in new-vehicle prices. We explore this approach further in Section 6. The core idea is that the underlying functions and parameters are static; they determine where the new equilibrium will end up but are not themselves a function of the equilibrium. Consider vehicle scrappage as an example: the equilibrium scrap rate of a particular vehicle is dependent on everything else in the system (e.g., prices and quantities of all new and used vehicles) and evolves in a dynamic way through time. A scrap *function*, on the other hand, is defined by an underlying relationship (here, the tendency to do more repairs on vehicles that are more valuable) that remains fixed.

The simulation tool we developed translates vehicle demand elasticities and scrappage elasticities into a time path of policy-relevant outcomes. For example, a new-vehicle own-price demand elasticity of −1 means that a 1% increase in new-vehicle price will result in a 1% reduction in the quantity of new vehicles demanded, all else equal. However, in a policy scenario context, it is not the case that all else remains equal. If a regulation raises new LDV prices by 1%, the effect on purchases of new vehicles is no longer the 1% decline suggested by the own-price demand elasticity because price expectations for used vehicles and scrappage rates are adjusting simultaneously with the new-vehicle price shock.

A dynamic model can address relevant questions regarding the impacts of changes in new-vehicle prices on new- and used-vehicle markets, scrappage rates, and the size and composition of the U.S. LDV inventory. Assuming the policy shock is long-lived, the effects on used-vehicle prices and scrappage evolve, likely strengthening as more vintages become directly affected over time.[13] Our simulation model shows the transition path as the vehicle inventory moves toward its new steady state. The differences between the short- and long-run impacts may be quite significant, making an aggregate simulation a practical tool for connecting empirical demand and scrappage elasticities taken from the literature to impacts on policy-relevant quantities.

The peer-reviewed economics literature has been able to provide empirical estimates of many of these underlying parameters and functions: these estimates are synthesized in Section 5. Section 6 then discusses how these elasticities from the literature might be used to inform parameter selection within the long-run simulation model we developed to assess outcomes in

[13] A countervailing effect, which also leads to interesting dynamics, can also be present to the extent compliance becomes easier as technology advances.

the new and used components of the inventory resulting from a policy shock. Because there is often disagreement and, in some cases, very little published work on key elasticities, we have constructed the simulation model to be very flexible. Sensitivity analyses can be conducted readily and running multiple simulations with economically plausible combinations of the underlying elasticities will return a range of outcomes that inherit the economic consistency of the underlying parameters.

SECTION 4.
DESCRIPTION OF STUDIES AND ATTRIBUTES ANALYZED

We conducted a systematic literature review for peer-reviewed publications and grey literature from academic and research institutions that appeared to be relevant based on our search terms (see text box below). We identified literature using three different search strategies. We reviewed the results of using these search terms within Google Scholar, JSTOR,[14] ResearchGate, and Science Direct search engines directly. In addition to these databases, we reviewed bibliographies of relevant literature to identify additional potential sources. We also reviewed the primary set of studies included in a previous review of the literature on willingness to pay for vehicle attributes conducted for EPA (Greene et al., 2018a) because we anticipated some overlap with the set of vehicle demand studies identified in that report.

Search parameters:

Types of literature: 1) peer-reviewed publications, 2) grey literature from academic/research institutions

Search engines: Google Scholar, JSTOR, ResearchGate, ScienceDirect

Publication years: 1995–present

Region: primarily U.S.

Search terms: new-vehicle prices, new automobile prices, vehicle replacement demand, used-vehicle price changes, new-vehicle sales, used vehicle sales, used automobile prices, pricing of new vehicles, pricing of new automobiles, motor vehicle pricing, vehicle scrappage, new-vehicle demand elasticity, demand for vehicle ownership, U.S. automobile market dynamics, automobiles secondary market, automobile market equilibrium, automobile prices, vehicle scrappage in the U.S.

4.1 Sample Description

We used the search parameters above to produce an initial pool of 37 papers. Among this sample, there were 25 that included information enabling estimation of the elasticity of demand for new vehicles, 16 that could inform estimates of the impacts of new-vehicle costs or prices on prices or sales of used vehicles, seven that estimated impacts of new- or used-vehicle prices or operating costs on scrappage of used vehicles, and four that identified factors influencing the total size of the combined new- and used-vehicle inventory.[15]

However, after conducting a more in-depth review and quantifying the estimates available from these studies, we ended up with only 19 different studies that provided 24 relevant elasticity estimates that met our search criteria. There were 10 estimates of elasticity of demand

[14] We used JSTOR's Text Analyzer to identify relevant literature within their database. This tool allows the user to upload a document/text for the Analyzer to "find the most significant topics and recommend(s) similar content." https://guides.jstor.org/howto-search/text-analyzer

[15] Some studies were identified as falling into multiple categories, so the sum of the individual categories exceeds the number of studies included.

for new vehicles from 10 studies, four estimates of the effects of vehicle prices on used vehicles from three studies (two estimates of the impacts of new-vehicle prices and two focused on the effects of used-vehicle prices), nine estimates of the impacts of vehicle prices on scrappage from seven studies, and one estimate of the effect of new-vehicle prices on total inventory size.[16] During peer review of the report, a reviewer identified an additional report providing an elasticity of demand for new vehicles that met our criteria for inclusion, resulting in our final count of 20 studies providing 25 elasticity values (11 estimates of elasticity of demand for new vehicles from 11 studies, four estimates of the effects of vehicle prices on used vehicles from three studies, nine estimates of the impacts of vehicle prices on scrappage from seven studies, and one estimate of the effect of new-vehicle prices on total inventory).

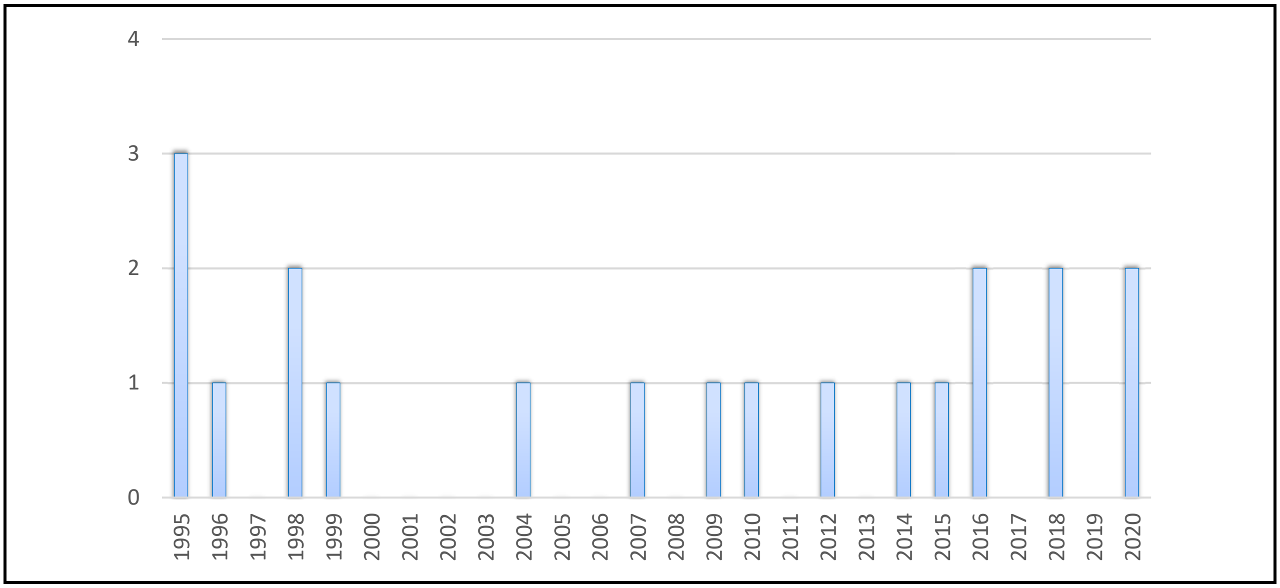
One of the biggest sources of the differences in number of studies included in the final quantitative analysis is that many of the studies identified as potentially relevant estimated demand at a more disaggregated level than our focus for this project. Many studies used vehicle type, model, or even trim-level data for new vehicles and did not include or did not report parameters for the outside option (e.g., purchasing a used vehicle or no vehicle rather than a new vehicle). Thus, they did not generate estimates of the aggregate-level market elasticity that we are focused on, but rather estimated demand elasticities that reflect substitution between different new vehicles. Although some of these papers reported “overall” demand elasticities, they are typically average or median individual elasticities, calculated across vehicle types, models, time, etc., which means they do not reflect the aggregate elasticities that we want to represent. For the purposes here, we are interested in the change in new-vehicle demand if many or all new-vehicle prices increase simultaneously, not what happens to demand for a single model or trim if only its price increases. As would be expected, the more disaggregated the vehicle sales data used, the higher the estimated elasticities tend to be. The fact that the elasticities differ in this way is entirely consistent with economic theory; more disaggregated choice sets (in terms of attributes, time of purchase, etc.) mean that the best substitutes for any given good within the choice set will be more similar to it (e.g., more substitution would be expected between sedan models or between makes of sedan than between new and used vehicles or between a personal passenger vehicle and alternative means of transportation). Heterogeneous consumers are more likely to be on the margin between purchasing one vehicle versus another because the way that the vehicle set is defined becomes more disaggregated and some products are more similar to one another

[16] Five studies provided multiple elasticity estimates that we incorporated into our summary, which explains why there are 25 elasticity estimates drawn from 20 studies.

for the attributes on which they are focusing their purchase decision. Thus, the own-price elasticity is higher because an increase in the price of the good will lead to more substitution.

Figure 4-1 shows the distribution of the final set of 20 studies by publication year, highlighting the relatively low and even distribution of papers in recent years.

Figure 4-1. Distribution of the Final Set of Papers Included by Year of Publication



As Table 4-1 details, most of the estimates came from peer-reviewed literature (75%); five papers from the main sample came from grey literature.

Table 4-1. Literature Summary Statistics Based on our Main Sample

Paper count	20
Literature type (out of 20)	
Peer reviewed	15
Grey	5
Parameter estimated (sums to more than 20 because some papers estimated multiple parameters)	
New-vehicle sales	11
Used-vehicle prices or sales	4
Scrappage	9
Total inventory size	1

4.2 List of Papers Identified

Table 4-2 lists each paper identified based on our review and summarizes the data used in each. The type of data used by each study is provided to highlight which studies derived estimates from stated preference versus collected market data. More than two-thirds of the papers in our sample implemented actual market data in their models. Market segment further provides insight into whether the studies used data to represent households or market aggregate. It also shows the transactions presented in the study (new, used, or both).

Table 4-2. List of Papers Included and Parameter Estimates Provided

Citation	Region	Type of Data	Market Segment
Alberini, Harrington, and McConnell (1998)	California	Market	Households, used vehicles
Bento, Goulder, Jacobsen, and von Haefen (2009)	United States	Survey	Households, new and used vehicles
Bento, Jacobsen, Knittel, and van Benthem (2020)	United States	Market	Households, new and used vehicles
Bento, Roth, and Zuo (2018)	United States	Market	Households, used vehicles
Berry, Levinsohn, and Pakes (2004)	United States	Survey	Households, new vehicles
Berry, Levinsohn, and Pakes (1995)	United States	Market	Market, new vehicles
Chen, Esteban, and Shum (2010)	United States	Market	Households, new and used vehicles
Dou and Linn (2020)	United States	Market	Households, new vehicles
Fischer, Harrington, and Parry (2007)	United States	Market	Market, new vehicles
Goldberg (1996)	United States	Survey	Market, new vehicles
Greenspan and Cohen (1999)	United States	Market	Market, used vehicles
Hahn (1995)	United States	Market	Market, used vehicles
Jacobsen and van Benthem (2015)	United States	Market	Households, used vehicles
Jayarajan, Siddarth, and Silva-Risso, 2018	Indiana and California	Market	Market, used vehicles
Knittel and Metaxoglou (2014)	United States	Market	Market, new vehicles
Leard (2021)	United States	Survey	Households, new vehicles
McAlinden et al. (2016)	United States	Market	Market, new vehicles
McCarthy (1996)	United States	Survey	Households, new vehicles
Miaou (1995)	United States	Market	Households, used vehicles
Selby and Kockelman (2012)	Texas	Survey	Households, used vehicles

SECTION 5.
LITERATURE SYNTHESIS

This section summarizes the findings of our review of the papers identified in Section 4. We have conducted a review of these papers to identify available estimates that can be used to predict one or more of the following:

- the effect of changes in new-vehicle prices or costs on new-vehicle sales,
- the effect of changes in new-vehicle costs or prices on prices or sales of used vehicles,
- the effect of changes in new- or used-vehicle prices or operating costs on scrappage of used vehicles, and
- the effect of the factors influencing the total size of the (combined new and used) vehicle inventory on the size of the inventory.

We compiled information on each article, including author(s), publication year, journal, years of data used in the analysis, the kind of data used (e.g., stated preference, revealed preference, market data), sample size, and methods used for analysis (e.g., nested logit, mixed logit) (provided in attached spreadsheet).

Despite the importance of the LDVs market to the U.S. economy, the empirical evidence for the measures of consumer responsiveness necessary for empirical implementation of our simulation model is quite limited. It is important to note that even in cases where several estimates are available, these estimates often have remaining shortcomings for the purpose of evaluating long-run relationships between new-vehicle and used-vehicle markets, scrappage, and overall U.S. vehicle inventory. For instance, many of the studies are more than a decade old, often relying on data that are even older. Vehicles are becoming more durable over time, while embedded vehicle technology is changing rapidly, which may decrease the substitutability between newer and older vehicles. Thus, older studies may not adequately capture current consumer behavior. In addition, it is reasonable to expect that the elasticity of demand for new vehicles may shrink as consumers get richer. In that case, reliance on older studies may tend to overestimate the new vehicle price elasticity in current vehicle markets. Another consideration is that many of the available studies from which elasticity parameters can be drawn or calculated are not primarily focused on the parameters that are of interest for this study. Although we believe it makes sense to use those parameters for the purposes of this study because they reflect the range of values implied by the available literature, these papers were not necessarily focused on identifying aggregate elasticities and may have chosen a different specification had they been focused on estimating aggregate market elasticities.

Unfortunately, available information from these papers is generally insufficient to characterize the distribution of these estimated elasticities. In many cases, the point estimate of the relevant elasticity is directly stated in the main body of the paper or a footnote. In other cases, we estimated the elasticity based on available information on parameters combined with assumptions that make it difficult to formally characterize the uncertainty associated with a given elasticity estimate. Thus, we focus throughout on reporting the point estimates available from each study.

The remainder of this section provides descriptions of the set of papers that provided relevant elasticities or sufficient information to generate elasticity estimates, organized by elasticity parameter, and summarizes our findings on the state of knowledge and level of agreement for each.[17]

5.1 Effect of Changes in New-Vehicle Prices or Costs on New-Vehicle Sales

The aggregate own-price elasticity for new vehicles is the parameter being examined that has the most estimates available from the literature. These elasticities capture substitution from new to used vehicles as well as to the outside good, defined here as choosing to travel by means other than a personal LDV (e.g., switching travel modes to public transit, bicycle, walking, or other options). Table 5-1 summarizes the studies included and their elasticity estimates, organized by category of estimate and ordered within those categories by year of publication.[18] We then briefly describe each of the studies incorporated and the findings, ordered in the same way. The elasticities in the first panel hold constant most other aspects of the equilibrium system, including equilibrium changes in used vehicle prices. They ask how new-vehicle sales change when new-vehicle prices alone change. The studies in the second panel develop simulation models that allow prices in the used market to also rise over time. These elasticities are, therefore, expected to be smaller in magnitude, along the lines of the discussion in Section 3 above and are similar in spirit to the policy elasticities we provide from our modeling. They do

[17] For those cases where parameter estimates were calculated by the report authors rather than being obtained directly from the referenced studies, spreadsheets showing calculations used to obtain elasticity estimates are available from the report authors upon request.

[18] A reviewer suggested adding Stock et al. (2018) to this summary table, but it did not meet our search criteria of peer-reviewed or high-quality grey literature published by a research institution, so we did not include it in Table 5-1 or in the text summarizing our primary findings on the range of estimates. However, we did add another sensitivity case to Appendix C with a much lower elasticity value (−0.10) to represent the value implied by Stock et al. (2018).

not allow changes in scrappage and other dynamics but are an important reference point for our estimates.

Table 5-1. Summary of Aggregate Own-Price Elasticities for New Vehicles

Study	Time Frame of Data Used	Elasticity
Aggregate own-price elasticity		
BLP (1995)	1971–1990	−1.08[a]
McCarthy (1996)	1989	−0.87
Goldberg (1998)	1984–1990	−0.90
Berry, Levinson, and Pakes (2004)	1993	−0.40[c]
Fischer, Harrington, and Parry (2007)	2000	−1.00
Bento et al. (2009)	2001	−1.27[b]
Knittel and Metaxoglou (2014)	1971–1990	−0.57
McAlinden et al. (2016)	1953–2013	−0.61
Dou and Linn (2020)	1996–2016	−0.78[a]
Leard (2021)	2014–2015	−0.37
Aggregate own-price elasticity after price effects in the used vehicle market		
Fischer, Harrington, and Parry (2007)	2000; calculated from calibrated model	−0.36
Chen, Esteban, and Shum (2010)	NA; calculated from calibrated model	−0.18[a]

[a] Author Calculations. Aggregate elasticity not reported by authors of the cited paper but was calculated using data from the paper (see text for additional details).

[b] Author Calculations. Aggregate elasticity not reported by authors of the cited paper, but we were able to access the model used in this paper and recompute the aggregate elasticity from the logit parameter estimates.

[c] We note that the authors of the study indicated this estimate relies especially strongly on functional forms and may not be well identified. In an alternative calculation, they instead considered a market elasticity of −1 (based on estimates from General Motors).

5.1.1 Aggregate Own-Price Elasticity of Demand for New Vehicles with Respect to Price of New Vehicles

BLP (1995) estimated disaggregated elasticities, including those to an outside good of not purchasing a new vehicle. Thus, although they did not report an aggregate elasticity, there was sufficient information available for us to calculate one. We calculated a simple average of the model-level price elasticities using the values reported in their Table V (−5.00) and used data reported in their Table VII to calculate the average substitution to the outside good (i.e., not purchasing a new vehicle) (21.53%). We then multiplied these values to estimate the aggregate own-price elasticity for new vehicles as −1.08. There are some important caveats to this calculation. We only have the sample of vehicles they reported in their tables and assumed it is representative of the full set of new vehicles available for sale. In addition, we made a simple assumption regarding average model-level elasticities and average substitution to the outside good, whereas we would ideally want to calculate share-weighted averages if sufficient data were reported. As an additional caveat, the authors noted (p. 881) that "the numbers [on substitution outside] still seem a bit large to us." This group of authors in a later work (Berry, Levinson, and Pakes, 2004) considered values of −0.40 and −1.00 for the aggregate elasticity.

McCarthy (1996) reported an estimate of the own-price elasticity for new vehicles, along with cross-price and income elasticities. They were focused on assessing the effects of accounting for perceived quality (based on an argument from the literature that the market price elasticity of demand is substantially biased downward when demand is not corrected for quality differences), though in the end found relatively little impact on their estimates. The estimate of the elasticity from their preferred model is −0.87.

Goldberg (1998) focused on assessing the effects of Corporate Average Fuel Economy (CAFE) standards on new-vehicle sales, prices, and fuel consumption. As part of this study, a discrete choice model of vehicle demand was estimated using micro data for 1984–1990 from the Consumer Expenditure Survey (CES). They estimated an aggregate elasticity of demand for new vehicles of −0.9.

Barry, Levinson, and Pakes (2004) estimated an aggregate elasticity of demand of −0.4 in their preferred model specification, combining micro and macro data, including survey data of vehicle buyers indicating what their second choice would have been had they not purchased the new vehicle that they bought. However, they also stated that "[o]n the basis of their experience, the staff at General Motors suggested that the aggregate (market) price elasticity in the market for new vehicles was near one," so Barry, Levinson, and Pakes (2004) also present outputs calibrated to match General Motors' estimate of −1.0.

Bento et al. (2009) did not report an own-price demand elasticity in their paper, but we were able to access the data and code used for the analysis conducted in that paper and applied it to estimate an aggregate own-price demand elasticity of −1.27. This is the most elastic estimate among any of the studies identified for inclusion in this report, perhaps connected to the cross-sectional nature of the variation and longer-run changes in demand that are implied. The study used data from the 2001 National Household Travel Survey and is identified from variation across locations in vehicle ownership costs and gasoline price. Places with high vehicle costs tend to have fewer vehicle sales, all else equal, due not only to substitution to the used market but also to longer run attributes of the location like transit availability and structure of cities.

Knittel and Metaxoglu (2014) employed a broad range of numerical methods, including many that do not perform especially well in minimizing their objective function. Focusing on the numerical method that performs best (producing the minimum value for the objective function) the elasticity estimate is −0.57. They presented a range of −0.41 to −1.74 for this elasticity across all numerical methods used.

McAlinden et al. (2016) used annual data from 1953–2013 to estimate the change in consumer spending on new vehicles as a function of income, new-vehicle prices, used-vehicle prices, consumer credit, interest rates, and total number of households. They found a short-run own-price elasticity for spending on new motor vehicles of −0.79. Applying a Koyck transformation, they estimated the long-run own-price elasticity to be −0.61. The authors noted that their estimate is lower than previous disaggregate, cross-sectional models that they reviewed, which they attributed to their inclusion of consumer credit and interest rate variables in their estimation.[19]

Dou and Linn (2020) estimated a 0.30% decline in new-vehicle sales from the imposition of a policy that raises the new-vehicle price by $108 ($90 in added cost and $18 in markup). Using data elsewhere in the paper on average vehicle prices, we calculated a 0.383% increase in price. The corresponding elasticity is −0.78. The purchase data used in the study are CES microdata from 1996–2016. They also examined used-vehicle sales but considered changes in transactions rather than changes in aggregate quantities or scrappage in that component of the analysis.

Leard (2021[20]) estimated a relatively inelastic response of new vehicle purchases to changes in new-vehicle prices among the papers included in our study, −0.37. The paper used second-choice data from a survey of new vehicle buyers. Leard (2021) argued that logit models such as used in McCarthy (1996) tend to produce unreasonably large substitution toward alternatives with large market shares (and here, in particular, toward not purchasing a new vehicle), so they may overstate consumer responsiveness to new-vehicle prices. He noted that in

[19] McAlinden et al. (2016) estimated a short-run elasticity of −1.31 when they estimated an alternative version of their model excluding consumer credit and interest rates as explanatory variables.

[20] There are multiple versions of this working paper available. We used the most recent version at the time of preparing this report, the May 2021 version. This version estimates a more elastic response than the initial version. It also no longer reported a cross-price elasticity between new and used vehicles that was present in earlier versions.

a given year the market share for not purchasing a vehicle is around 90% and that logit model specifications implicitly assume little difference between new vehicle buyers and those who do not purchase a new vehicle, an assumption not supported by data.

5.1.2 Aggregate Own-Price Elasticity of Demand for New Vehicles with Respect to Price of New Vehicles, Allowing for Price Effects in the Used Market

Fischer, Harrington, and Parry (2007) applied a model of the U.S. vehicle inventory and simulated changes in the inventory over time and accounted for adjustments in used-vehicle prices. They estimated a long-run elasticity of −0.36 as their primary case, though also conducted sensitivity analyses with elasticities of 0 and −0.8.

Chen, Esteban, and Shum (2010) estimated an increase of 3% in new-vehicle sales when new-vehicle taxes are reduced by 30%. The tax-inclusive price of a new vehicle falls by 17% in their scenario, implying an aggregate new-vehicle price elasticity of −0.18. Their model allowed used-vehicle prices to adjust endogenously along the lines of the interactions we explore below, though it held vehicle lifetimes fixed.

5.1.3 Summary

Even in the category where we have the most empirical estimates available from the literature, the direct own-price elasticity of demand for new vehicles, relatively few studies provided aggregate elasticities. The magnitudes estimated are relatively consistent, though. Demand elasticity estimates range from −0.37 to −1.27, though six out of eight are inelastic (ranging from −0.37 to −0.90). Studies using second-choice micro data (e.g., Barry, Levinson, and Pakes [2004], Leard [2021]) tended to have the lowest elasticity estimates.

However, the data used in these studies tend to be quite old, with only two of the studies identified using data more recent than 2001. To the extent that the responsiveness of vehicle demand has changed in the last 20 years, most of these studies are not reflective of current market conditions. In addition, a number of these studies relied on panel data with very short time series. There may not be enough variation in the panel to identify the choice of an outside option. It is also the case that many of these studies were not necessarily focused on estimating the demand elasticity, and authors may not have considered what variation is determining the estimate of the parameters for the outside option.

As expected given the relationship between the new- and used-vehicle markets, the available elasticities of new-vehicle demand when used-vehicle prices can adjust (−0.18, −0.36) indicate less responsiveness. These elasticities reflect medium-term responsiveness, allowing for markets to adjust to a new equilibrium. Both available estimates fall below the lower end of the range for standard demand elasticities measured when the prices of substitutes are fixed. The model developed here additionally accounts for expectations and allows endogenous changes in scrappage but is similar in spirit; the two elasticities from the literature support the core intuition that accounting for market interactions between new and used vehicles leads to substantially smaller elasticity values.

5.2 Effect of Changes in Vehicle Costs or Prices on Prices or Sales of Used Vehicles

Table 5-2 summarizes the studies identified that provided estimates of the effects of changes in new- or used-vehicle prices on the used-vehicle market, in terms of either prices or quantities. A very limited number of such studies are available. The table is organized by category of estimate and the discussion follows this organization as well. Although our focus was on the effects of new-vehicle prices on the used-vehicle market, we included a study examining the relationship between used-vehicle prices and used-vehicle sales.

Table 5-2. Summary of Estimated Effects of Changes in New- or Used-Vehicle Prices on Used-Vehicle Markets

Study	Time Frame of Data Used	Elasticity
Elasticity of used-vehicle price with respect to new-vehicle price:		
Chen, Esteban, and Shum (2010)	NA; calculated from calibrated model	1.69
Average own-price elasticity, used vehicles:		
Jayarajan et al. (2018)	2003–2006	−1.23
Bento et al. (2009)	2001	−0.54
Elasticity of used-vehicle inventory with respect to new-vehicle price, long run:		
Bento et al. (2009)	2001	−0.08
Bento et al. (2020)	NA; calculated from simulation model	−0.12

5.2.1 Elasticity of Used-Vehicle Price with Respect to New-Vehicle Price

Chen, Esteban, and Shum (2010) estimated a 28.8% decline in used-vehicle prices when the new-vehicle price declines 17%. This estimate is representative of a long-run equilibrium and corresponds to an elasticity of 1.69. As expected, changes in new-vehicle prices lead to changes in the same direction in prices in the used-vehicle market. Given the smaller value of used vehicles relative to new, the corresponding derivative is smaller than the elasticity and is 0.91 (a $1 increase in new-vehicle price corresponds to a $0.91 increase in used-vehicle price).

5.2.2 Own-Price Elasticity for Used Vehicles with Respect to Price of Used Vehicles

Jayarajan et al. (2018) reported an average elasticity across estimates at the model level. We did not include average estimates for individual new vehicles because aggregate elasticities were more available but provide these because so few studies have examined demand elasticities of any type in the used market. Their estimate of own-price elasticity for used vehicles ranged from −0.75 to −1.93 with a mean of −1.23. This is larger than most elasticity estimates for new vehicles but is not directly comparable to the estimates provided above for new vehicles because this value represents an average across model-level elasticities rather than an aggregate elasticity for used vehicles. They find that price changes of new vehicles have a substantially larger effect on used-vehicle markets than vice versa.

Bento et al. (2009) also reported model-level price elasticities among used vehicles: the average vehicle-level elasticity among all used vehicles was −0.54. Newer used vehicles appear more elastic (with a reported average elasticity of −1.01) and are perhaps more comparable with the sample in Jayarajan et al. (2018). In both papers the demand elasticity reported reflects total consumer demand for a used vintage at a given price irrespective of how that demand might be met. The used vehicle quantities we work with are aggregate values and reflect changes in the total quantity of vehicles in the system rather than numbers of transactions among individuals.[21]

5.2.3 Elasticity of Used-Vehicle Quantities with Respect to Price of New Vehicles

Bento et al. (2020) took as given that the aggregate elasticity of demand for new vehicles is −0.21 (from a recent National Highway Traffic Safety Administration rulemaking). They then constructed bounds on the elasticity of the size of the used inventory (also in long-run equilibrium) with respect to new-vehicle prices. The most elastic the long-run response of the used-vehicle inventory can be in their study is the value used for the long-run elasticity of demand for new vehicles (−0.21) if there is no reaction at all in equilibrium scrappage. This refers to a long-run equilibrium where the proportionate change in new-vehicle sales year after year (with no change in scrappage rates) eventually leads to the same percentage change in the total inventory. It is also possible that scrappage rates decline by so much that all the lost new vehicles are replaced by extending the life of used ones: this is the upper bound and evaluates to

[21] In practice, used vehicle demand can be met by maintaining an existing vehicle (not leading to a transaction) or buying one from someone else who has maintained it (leading to a transaction). The papers cited, and the model here, track the total of the two sources together.

0.016 in the example. The paper then estimated where within these two bounds the true used inventory elasticity likely falls. For a range of scrappage elasticities between −0.5 and −1.0, the long-run used inventory elasticity ranged between −0.14 and −0.10. These estimates were all constructed relative to the new-vehicle demand elasticity and scale directly with it. Because the new vehicle elasticity used in Bento et al. (2020) is lower than many in the literature (Table 5-1 above) perhaps the most relevant finding here is that the used-vehicle elasticity was estimated to be roughly one-half (i.e., −0.12 /−0.21 = 0.57) the magnitude of the new-vehicle elasticity.

5.2.4 Summary

Given that we identified very few studies in the three categories of elasticity estimates for used-vehicle markets (and that the studies examining own-price elasticities for used vehicles reported average rather than aggregate values), it is not possible to assess the degree of consensus in the literature. Further exploration of the aggregate response of used-vehicle markets to changes in new- and used-vehicle prices appears to be an important gap in the literature.

5.3 Effect of Changes in New- or Used-Vehicle Prices or Operating Costs on Scrappage of Used Vehicles

Table 5-3 lists each paper identified by our review providing a relevant estimate of the scrappage elasticity, separated into those assessing responsiveness of scrappage to used- versus new-vehicle prices. We then briefly summarize each of the studies incorporated, following the same order. There is substantial variation in the methods used to estimate responsiveness of scrappage to vehicle prices and in the estimates provided. A particularly important distinction is between those studies that are estimating scrappage econometrically and those that are conducting simulations of the response to a bounty program encouraging vehicle retirement. An important caveat of studies looking at a bounty for scrappage lies in the temporary nature of the program: it may be that a short-lived, salient subsidy will quickly harvest a stock of "almost-scrapped" vehicles, overstating the elasticity. The elasticities implied by the papers relying on simulations based on assumed data or a representative base year are very sensitive to the assumptions we used to calculate them. Based on calculations using what we think are reasonable central assumptions, these papers generate the highest and lowest elasticities among our sample. Overall, we question the reliability of these models for our purpose of generating aggregate scrappage elasticities and emphasize the econometrically estimated values for the purposes of selecting the range of scrappage elasticities used in our simulations.

Table 5-3. Summary of Scrappage Elasticities from Literature

Study	Time Frame of Data Used	Elasticity
Scrappage with respect to used-vehicle prices		
Hahn (1995)	1993; calculated from simulation	−1.14[a]
Miaou (1995)	1965–1992	−0.91
Alberini, Harrington, and McConnell (1998)	NA; calculated from simulation	−2.97[a]
Greenspan and Cohen (1999)	1973–1991	−0.82
Selby and Kockelman (2012)	2009; calculated from simulation	−0.01[a]
Jacobsen and van Benthem (2015)	1999–2009	−0.69
Bento, Roth, and Zuo (2018)	1981–2014	−0.36
Scrappage with respect to new-vehicle prices		
Miaou (1995)	1965–1992	−0.21
Greenspan and Cohen (1999)	1973–1991	−0.82

[a] Author Calculations. Aggregate elasticity not reported by authors of the cited paper but was calculated using data from the paper (see text for additional details).

Note: The three papers that generated results using simulation models of bounty programs to encourage retirement of older vehicles resulted in values that were quite different from the econometrically estimated values in the other studies. For each of the three, we had to calculate elasticities based on a combination of values presented in the paper and our assumptions, and we found that elasticities were very sensitive to our assumptions. Therefore, we have less confidence in the elasticities calculated from those three studies and focus on the econometrically estimated values in developing the range of values used in our model simulations.

5.3.1 Elasticity of Aggregate Scrappage with Respect to Average Price of Used Vehicles

In Hahn's (1995) Table 2, he relates an exogenous "bounty" (subsidy to scrappage) to changes in the absolute number of vehicles scrapped relative to a baseline, reflecting the short-run response. In a simple theoretical setting, a $1 subsidy to scrapping a vehicle should have the same effect as reducing the payoff from not scrapping a vehicle (i.e., the price the used vehicle would bring in the market) by $1. The challenge in converting the table to an elasticity is that the paper does not report the baseline value of scrappage or the baseline price of used vehicles, so both of those must be inferred to convert the level changes into an elasticity. Based on our assumptions, the elasticity was estimated to be −1.14, but one can potentially get very different elasticities by making alternative assumptions.

Miaou (1995) reported estimated elasticities directly, with an estimate of −0.91 for the elasticity of equilibrium scrappage. This paper looked at correlations in an equilibrium time series without attempting to separate supply and demand curves.

As in Hahn (1995), Alberini, Harrington, and McConnell (1998) related an exogenous bounty to changes in the number of vehicles scrapped (summarized in Figure 3b of their paper) within a simulation model. In a simple theoretical setting, a $1 subsidy to scrapping a vehicle should have the same effect as reducing the payoff from not scrapping a vehicle (i.e., the price the used vehicle would bring in the market) by $1. Based on the average value of used vehicles that could potentially be scrapped and the change in scrappage between a bounty of $0 and $1,000, we estimated an elasticity of −2.97.

Greenspan and Cohen (1999) also did not directly provide an elasticity estimate, but one can be calculated based on the information provided in footnote 22 of their paper, where they noted that a 1.9% increase in the ratio of the consumer price index (CPI) for repairs to the CPI for new vehicles reduced scrappage by 150,000 vehicles (1.56%). This led directly to the elasticity of −0.82. Note that the repair cost elasticity is −1 times the used-vehicle price elasticity under the (typical) assumption that vehicles are scrapped when the repair cost exceeds the vehicle's value. A 1% increase in repair cost for vehicles around the margin of scrappage has the same effect as reducing the value of those used vehicles by 1% (because repair cost and vehicle value are equal at the scrap margin by definition). In turn, this relationship means that the functional form imposed in the estimation here (namely that the cost of repairs and new vehicles enter inversely to one another) implicitly restricts new-price and used-price elasticities to be the same.

Selby and Kockelman (2012) simulates 5,000 households' vehicle-purchasing decisions over time based on survey data collected from Austin, Texas, in 2009. The authors conducted a few different simulations, including one looking at scrappage incentives. They did not report scrappage (or other) elasticities but did provide some of the information needed to calculate them. An important qualification in this exercise is that the way scrappage is presented appears to be unusual: When the scrappage subsidy increases by $2,000, for example, new-vehicle sales change very little, but the average age of vehicles reported increases. This paper appears to be defining scrappage (e.g., in Table 6) as vehicles that collect the bounty at the simulated auctions, while a more typical definition would define scrappage as all vehicles removed from the vehicle inventory regardless of cause. When we incorporated assumptions to translate the reported changes into aggregate scrappage, our central estimate of the scrappage elasticity appeared to be quite small relative to the literature, −0.012. We have less confidence in this calculated value than other scrappage elasticities presented in this section.

Jacobsen and van Benthem (2015) used data disaggregated at the level of make-model-age; the −0.69 in the table above is an average that can easily be disaggregated by age, class, make, etc. (e.g., columns 2–5 of Table 3 in their paper). Identification used an IV approach and included a range of fixed effects to remove aggregate shocks (age-year and make-model-age fixed effects in the main specification). The IV approach is aimed explicitly at tracing out a supply curve for used vehicles (i.e., the "not-scrapped" vehicles).

Bento, Roth, and Zuo (2018) used annual data on average used-vehicle price and aggregate scrappage. A structural approach (related to that in Greenspan and Cohen [1999]) is taken to identify different drivers of scrappage. The structural model included the prices of used vehicles on the right-hand side (where the −0.36 elasticity we report in the table comes from): higher used prices led to less scrappage.

5.3.2 Elasticity of Aggregate Scrappage with Respect to Average Price of New Vehicles

Miaou (1995) separately estimated an elasticity of equilibrium scrappage with respect to the average price of new vehicles. Their estimate was −0.21, less elastic than their estimated elasticity with respect to the price of used vehicles (−0.91).

As noted above, the functional form imposed by Greenspan and Cohen (1999) implicitly restricted scrappage elasticities with respect to new- and used-vehicle prices to be the same. The elasticity from Greenspan and Cohen (1999) is −0.82 and is reported again in this (elasticity with respect to new-vehicle price) section.

We note that the estimates in Miaou (1995) and Greenspan and Cohen (1999) reflect correlations in equilibrium time series rather than separate estimation of supply or demand curves.

5.3.3 Summary

There is a wide range of scrappage elasticity estimates with respect to used-vehicle prices in the literature, though we have less confidence in some of those that fall at the extremes of our range. In particular, elasticities calculated from the studies that rely on simulations or bounties (Hahn, 1995; Alberini, Harrington, and McConnell, 1998; and Selby and Kockelman, 2012) are more dependent on assumptions and interpretation and can change considerably with changes in assumptions. For the other four studies examining scrappage with respect to used-vehicle prices, the range is much tighter, from −0.36 to −0.91. There were only two studies examining scrappage with respect to new-vehicle prices, which fell in a similar range (−0.21, −0.82) to those for used-vehicle prices. To the extent there is a strong connection between new and used prices (as suggested in Table 2 and in the equilibrium simulations in Jacobsen and van Benthem [2015]) the tight link between the new- and used-price elasticities of scrappage is expected.

5.4 Effect of the Factors Influencing the Total Size of the (Combined New and Used) Vehicle Inventory on the Size of the Inventory

Table 5-4 lists the one paper identified as assessing the responsiveness of total inventory size to new-vehicle price based on our review.

Table 5-4. Summary of Estimated Vehicle Inventory Elasticities

Study	Time Frame of Data Used	Elasticity
Aggregate elasticity, total inventory with respect to aggregate vehicle price		
Bento et al. (2009)	2001	−0.14[a]

[a] Author Calculations. Aggregate elasticity was not reported by authors of the cited paper, but we were able to access the model used in this paper and recompute the aggregate elasticity from the logit parameter estimates.

Bento et al. (2009) estimated a demand system but did not report the full matrix of own- and cross-price elasticities. However, we were able to access the logit model code and data used by Bento et al. (2009) and recompute the aggregate elasticity based on the full matrix using base parameter estimates. This calculation provided an estimated elasticity value of −0.14, implying that a 1% increase in the price of new vehicles would result in a reduction in the total U.S. LDV inventory of 0.14%.

5.4.1 Summary

We found only a single study that met our criteria for providing sufficient information to calculate an aggregate inventory elasticity. Along with additional focus on the responsiveness of used-vehicle markets to new-vehicle prices, assessing interactions between new and used markets and implications for the U.S. vehicle inventory is another area that appears to be an important area for future research. Because vehicles are durable goods, a key component of the net impacts of a policy or regulation is these interactions between new and used markets, but these interactions have been less studied than the demand for new vehicles and scrappage decisions.

5.5 Other Related Parameter Estimates

As noted above, a number of studies provided estimates of elasticities for new vehicles at a disaggregated level, typically estimating elasticities in the range of −1.7 to −5.0. However, we could not directly make use of the majority of these studies because they did not include (or did not report) an outside good. Thus, their elasticity estimates largely reflect substitution between different types or models of new vehicles rather than an aggregate demand response when all new vehicles become more expensive.

Busse, Knittel, and Zettelmeyer (2013) investigated the effect of gasoline prices on new- and used-vehicle market shares and prices. There is a unit sales regression (Table 7 in their paper) that allows us to compute the short-run response of aggregate new-vehicle sales to a $1 increase in the price of gasoline. Based on their estimated parameters, we calculated the short-run elasticity of demand for new-vehicle sales with respect to gasoline price to be −0.13. Unfortunately, a similar exercise for used vehicles is not possible because the used-vehicle data reflect changes in vehicles transacted, not changes in the aggregate size of the used inventory. The response of new-vehicle sales to gasoline prices is related to what we are focused on in this review but does not directly address the question of elasticity with respect to total operating costs (given that fuel costs account for only a portion of operating costs). Finally, Dou and Linn (2020) estimated the elasticity of new-vehicle purchases with respect to CAFE policy stringency to be −0.3. Like Busse, Knittel, and Zettelmeyer (2013), however, this does not directly allow us to get at the responsiveness of new vehicle purchases to changes in operating costs.

In addition to estimating an own-price response for new vehicles, Leard (2021) also estimated responsiveness to own-cost per mile. The new vehicle market cost per mile elasticity is defined as the percentage change in aggregate new-vehicle sales due to a 1% increase in the cost per mile of all new vehicles and was estimated as −0.20. The analysis defines cost per mile as the price of gasoline divided by fuel economy. Direct comparison of this elasticity with the price elasticities in Section 5.1 would need to consider the fraction of total ownership and operating cost embedded in vehicle price relative to gasoline expenditure, as well as behavioral effects related to the timing of the different expenses. Given the lack of data on the former and uncertainty involved in the latter, this elasticity is likely not directly applicable here.

SECTION 6.
LONG-RUN MODELING OF THE AGGREGATE U.S. VEHICLE INVENTORY

The longevity of vehicles and the ability to buy and sell them as they age create a dynamic setting where short-run and long-run impacts from a policy can differ quite significantly from the impacts of a transient shock to prices. In particular, demand elasticities capture the impact of shocks to individual prices, but an equilibrium that also considers scrappage and asset prices is needed to measure the effect of a sustained regulation placed on a durable good. Here we describe a quantitative long-run steady-state equilibrium that allows us to compute policy elasticities, accounting for dynamics in the vehicle stock and corresponding to a given set of demand elasticities and scrappage elasticities. We focus on keeping the setting as parsimonious and transparent as possible, limiting inputs to those needed to determine equilibrium vehicle stocks. This model does not address the transition to the long-run equilibrium; that transition is addressed in Section 8.

We begin with core notation for quantities, prices, and ownership costs and then describe demand, supply, and equilibrium. Of particular note is the presence of two price vectors: one describing asset values and the other describing annual depreciation (and other ownership costs). In the long-run equilibrium discussed in this section, these two vectors are a simple transformation of one another: If vehicle lifetimes increase, the fraction of the original purchase price that gets depreciated in any 1 year becomes correspondingly smaller. Keeping the two sets of prices separate becomes more important for the dynamic problem (Section 8) where expectations and timing create a more complex relationship.

6.1 Model Notation

a indexes vehicle age. Varies between 0 (new) and A (we will set $A = 30$ in the quantitative analysis that follows)

q_a number of vehicles of age *a* in equilibrium, so $\sum_a q_a$ is the total long-run vehicle stock

q_a^D aggregate number of vehicles of age *a* demanded by the representative consumer

q_a^S aggregate number of vehicles of age *a* supplied

s_a equilibrium probability that vehicle is scrapped between ages *a-1* and *a*. $s_a \equiv \frac{q_{a-1}-q_a}{q_{a-1}}$

h_a average repairs needed to keep a vehicle of age *a* from being scrapped

p_a asset value (price if being sold in the market) of a vehicle of age *a*

r_a ownership cost of a vehicle of age a, includes depreciation and repairs, h_a

6.2 Vehicle Demand

The economics literature estimates elasticities of demand for vehicles using price shocks that either explicitly or implicitly with the aid of a structural approach, alter one vehicle price at a time. These price shocks can then be used to trace out the own- and cross-price elasticities of demand for a given vehicle. However, the elasticities for individual vehicles measured by this approach do not provide clear signals about an elasticity of demand for new vehicles in the aggregate. The alternative choice for each individual vehicle includes other new vehicle models and the outside good (not purchasing a new vehicle, substituting a used vehicle or means of transportation other than an LDV). Thus, demand for an individual model is likely to be much more elastic than demand for a generic new vehicle. For our analysis of the age profile and overall size of the vehicle stock we used a high level of aggregation (considering a representative vehicle of each age a) and employed a range of demand elasticities from the literature that reflect the responsiveness of a representative household to price shifts across new and used vehicles.[22]

The age-level aggregation means we cannot track compositional effects within a given age; if a new vintage is 10% more fuel efficient than an old vintage, then we assumed it remains that way as it ages. We address the dynamics of how the new vintage as a whole moves through the fleet. To the extent a policy has effects on most models within a vintage (e.g., a footprint-based fuel economy policy that requires simultaneous improvements across models), our aggregation captures the setting well. If a policy affects only a few models, then we might instead expect changes in scrappage and age profiles to be more pronounced in those models; our aggregate model would capture only a more muted average response for the vintage. Computational costs and lack of availability of detailed elasticities prevent us from writing a more disaggregate model here, but extensions of the method to account for more vehicle types may be feasible.

We assumed that the demand system is stable over time such that elasticities and relative vehicle values in the utility function remain fixed. Elasticities were determined from the literature and relative vehicle values in utility were implied by observed differences in ownership cost of vehicles at different ages. In part, the assumption of stable utility is practical; there are no

[22] While the demand-elasticity setting maintains generality in many respects, it does require us to abstract from transaction costs. Any single household might keep a vehicle for several years to reduce transaction costs (effectively choosing it through a sequence of ages), something we cannot model explicitly with a representative agent. We note, however, that the policies we consider here tend to increase vehicle lifetimes only slightly, meaning there are unlikely to be significant changes in overall numbers of transactions. In the short run (explored in Section 8), transactions costs could potentially enter more importantly as vehicles get reshuffled.

readily available estimates of how elasticities and relative utility might evolve with policy. We do note, however, that electrification of the vehicle market could introduce important changes. Because new electric vehicles will likely come with attractive new gadgets and safety features in addition to expanded range, this could widen the gulf in utility between new and old vintages, making new-vehicle buyers less willing to substitute to an old (gasoline-powered) vehicle. On the other hand, electrification might also narrow the gap in utility between new and old vintages: to the extent the new technology is not trusted, new-vehicle buyers might instead substitute more easily to an older gasoline model.

For simplicity the utility structure here also abstracts from a separate choice of miles driven, holding the number of miles driven by any particular age of vehicle fixed. To the extent people buy fewer new vehicles or retire more used ones, they would implicitly be choosing to drive fewer miles. We focus attention on creating a dynamically consistent and parsimonious translation between demand and scrappage elasticities and outcomes to do with the stock and age profile of vehicles. This can serve as an input into larger analyses, which could add functional forms and assumptions to do with the rebound effect to model overall outcomes like gasoline use and miles driven. A key limitation of the work here is that, to the extent changes in intensity of vehicle use are large, we do not capture the interaction between intensity of use and increased depreciation and scrappage.[23]

We write the demand system over vehicles of different ages and an outside numeraire good in terms of the ownership costs associated with choosing each vehicle age, $\boldsymbol{r} \equiv [r_0, r_1, \dots, r_A]$. Modeling ownership cost as the variable of interest to the consumer follows the approach in Bento et al. (2009) and is important when allowing choices to be made between new and used vehicles. For the literature that examines choice among different new vehicle models (excluding used vehicles from the choice set), purchase price is the more typical measure and produces equivalent elasticities.[24]

To represent the system of demand elasticities as flexibly, yet parsimoniously, as possible, we followed Deaton and Muellbauer (1980). Their demand system approximates any utility-consistent setting using a set of $n(n-1)/2$ free elasticity parameters (the minimum

[23] Knittel and Sallee have a working paper (2021) that shows most vehicle depreciation comes from time, not miles, which suggests that effects on vehicle depreciation and scrappage may be small even if changes in intensity of vehicle use (i.e., the rebound effect) are relatively large.

[24] The equivalence in the case of a new-vehicle-only analysis holds when residual value after a typical holding period is a constant fraction of the purchase price. Then, a 1% increase in the purchase price equates to a 1% increase in the ownership cost (i.e., purchase price less residual value), so the relevant demand elasticities are identical.

required for a complete Slutsky matrix) and is fully consistent with utility theory.[25] n in our setting is equal to $A + 2$, that is: new vehicles, used vehicles of ages 1 through A, and a numeraire outside good we will label N. Rewriting the Deaton and Muellbauer system in our notation (and simplifying it to abstract from income effects), we have demand for vehicles given by:

$$q_a^D(\boldsymbol{r}) = \frac{M}{r_a}\left(\beta_a + \sum_{\hat{a}=0}^{A} \theta_{a\hat{a}} \ln(r_{\hat{a}})\right) \tag{6-1}$$

and demand for the numeraire given by:

$$q_N^D(\boldsymbol{r}) = M\left(\beta_N + \sum_{\hat{a}=0}^{A} \theta_{N\hat{a}} \ln(r_{\hat{a}})\right) \tag{6-2}$$

where M is aggregate expenditure and the set of β parameters determines baseline expenditure shares and can be readily calculated from data on the age structure and depreciation of the vehicle stock. In a straightforward extension, the vehicle stock can also be allowed to grow over time at a rate κ, though this has little effect on the overall pattern of results.[26] The $n \times n$ matrix of θ parameters controls derivatives with respect to prices and maps directly into any matrix of own- and cross-price elasticities. We took elasticity estimates from the empirical economics literature for the estimates presented here; performing sensitivity analyses and considering bounds on demand elasticities are straightforward. The relationship between any θ_{jk} and the corresponding demand elasticity ϵ_{jk} (where j and k index the full set of new and used vehicles plus the numeraire) is:

$$\epsilon_{jk} = \frac{\theta_{jk} M}{r_j q_j} \text{ for cross-price elasticities}$$

$$\epsilon_{jj} = \frac{\theta_{jj} M}{r_j q_j} - 1 \text{ for own-price elasticities} \tag{6-3}$$

Deaton and Muellbauer (1980) showed how the basic restrictions on θ_{jk} from utility theory (symmetry, invariance to units, and adding up) also translate easily in their setting. In particular, the requirements for a consistent demand system are:

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[25] Further, the system can be extended to allow for fully flexible income effects if an approximation to the price index is used. Deaton and Muellbauer showed that even this more complicated "almost ideal" version maintains full consistency with economic theory and underlying utility. The potential to explore income effects in the vehicle choice setting may be a useful future extension and would likely be easily implemented. We did not do so here because empirical estimates of income effects are even sparser than those of demand elasticities.

[26] Because the demand system is homothetic, growth in the vehicle stock can be introduced by allowing M to increase at rate κ. The long-run steady state then involves symmetric growth (at rate κ) in demand at each vehicle age, which can be satisfied with the same system of steady-state prices and scrappage because the inflow of vehicles each year (i.e., historical new vehicle sales) is rising at the same rate.

$$\theta_{jk} = \theta_{kj,} \Sigma_j \theta_{jk} = 0 \text{ for all } k, \text{and } \Sigma_j \beta_j = 1 \qquad \text{(6-4)}$$

This flexible system for imposing demand elasticities laid out in equations (6-3) and (6-4) has three main advantages. First, it allows for a very intuitive set of inputs (elasticities directly, as opposed to structural parameters). Second, generating numerous scenarios and experimenting with bounding or Monte-Carlo type analyses becomes more straightforward. And finally, general theoretical restrictions on utility are readily satisfied.

6.3 Vehicle Supply

Supply of the numeraire *N* is competitive and meets demand at the price of one. Supply functions for vehicles of different ages define the other side of the market and allow us to solve for long-run equilibrium effects on the vehicle stock.

The price of a new vehicle is taken as given in the model. A change in this price leads to changes in purchases and retirements and, therefore, to changes in the size and age profile of the overall vehicle stock. Taken most directly, the effect of an increase in new-vehicle purchase price could reflect a simple tax. Conceptually, however, the model can also include much richer policies by using the price increase to represent a net loss in perceived indirect utility coming from multiple sources. For example, consider a policy that raises the price of vehicles by \$10, reduces horsepower such that the consumer loses \$3 worth of utility, and saves the consumer \$15 on gasoline. If this consumer is fully rational, they would recognize that this combination of changes has increased their indirect utility from the new vehicle and would view it as equivalent to a \$2 subsidy for this vehicle. However, suppose the consumer is inattentive to gasoline saving and only perceives \$10 worth of the \$15 in savings. $\$10 + 3 - 10 = \$3$; the effect on a potential purchaser of this new vehicle is as if they faced a new-vehicle tax of \$3. For a fuel-economy or electric vehicle policy, these three categories can reflect most of the as-if price increase: increased production cost (positive), willingness to pay for attribute changes (positive if valuable attributes are lost), and perceived fuel savings (negative).

We note that changes in the competitiveness of the new-vehicle market would also lead to changes in new-vehicle prices faced by consumers. To capture this type of change, the generalized cost faced by new-vehicle buyers (an input to the present model) would need to be adjusted up or down. We do not have a strong prior on if policy is likely to increase or decrease market power, so we believe a neutral assumption that markups remain fixed is reasonable. In this setting, the change in generalized cost from a policy would only need to reflect changes in production cost (with appropriate markups) and attributes.

If used versions of vehicles were not an important component of the market and new-vehicle supply were perfectly elastic as above, then demand elasticity estimates alone are enough to predict what will happen when there is a cost increase due to policy. The effect of the policy in that world can just be read directly from the estimated cost increase and the demand elasticity. The core element that makes the vehicle market unique, however, is the fact that used vehicles are not perfectly elastically supplied. When a particular used model's price rises, more of that model becomes available (e.g., because scrap dealers, insurance companies, and mechanics decide to repair and sell more of them as vehicles instead of as scrap metal). However, this effect is limited by the overall number of vehicles of a certain vintage and model that are available in the system. Because the elasticity of supply for used models appears to be intermediate, neither very close to zero nor very close to infinity, the equilibrium outcome for these vehicles depends importantly on *both* the elasticity of demand and supply (where used-vehicle supply is just the inverse of scrappage).

Jacobsen and van Benthem (2015) showed that a straightforward scrappage function can be built from an underlying distribution of repair cost shocks (e.g., costs from mechanical failures and accidents) and the assumption that scrap occurs whenever the realized repair shock exceeds the value of the vehicle.[27] Any underlying distribution of cost shocks with positive support corresponds to a scrap function $s_a(p_a)$ that slopes downward as vehicle values increase. The corresponding scrap elasticity γ is also strictly negative, and we followed Jacobsen and van Benthem (2015) to define it as $\gamma \equiv \frac{\partial s_a}{\partial p_a}\frac{p_a}{s_a}$.

To keep our equilibrium calculation as straightforward as possible, we considered a constant elasticity scrappage function taking only two parameters: one parameter that scales scrappage levels in the baseline and another that directly sets the scrappage elasticity. Following Jacobsen and van Benthem (2015):

$$s_a = b_a \cdot (p_a)^{\Upsilon} \tag{6-5}$$

where b_a is the baseline scale term and $\gamma < 0$ is the scrappage elasticity (defined as the percentage change in scrappage for each 1% increase in vehicle value). Supply of vehicles at any given age is then just the originally manufactured quantity minus the cumulative effects of scrappage. In the long run, where manufacturing and scrappage are stable (or growing at a steady

[27] More complex scrappage functions could also be introduced, but we believe the repair-cost driven function captures the essence of the decision. The presence of transactions costs, for example, could lead to a more complicated scrappage function that directly involves the prices of other, perhaps even new, vehicles. Jacobsen and van Benthem (2015) presented a range of arguments why the prices of other vehicles are unlikely to be important direct determinants of scrap.

rate) from year to year, we have vehicle supply at any age $a \geq 1$ determined by cumulative survival to that point: $q_a^S = q_0 \prod_{\hat{a}=1}^{a}(1 - s_{\hat{a}})$. Plugging in, supply at any age can be written as a function of q_0 and the vector of asset values $\boldsymbol{p}$:

$$q_a^S(q_0, \boldsymbol{p}) = q_0 \prod_{\hat{a}=1}^{a}(1 - b_{\hat{a}} \cdot (p_{\hat{a}})^{\gamma}) \quad (6\text{-}6)$$

6.4 Market Equilibrium

To measure the effect of a policy in the long run, we examined the equilibrium where prices and scrap rates have reached a new stable level (in the presence of a sustained policy) and where demand for vehicles at each age equals supply. In the short and medium runs and cases where the policy itself fluctuates, a more complex dynamic transition occurs where prices and scrappage evolve from 1 year to the next (explored later in Section 8).

To formalize, we want to solve for the long-run effect of a regulation that increases the price of new vehicles (or equivalently reduces net indirect utility of the purchase) by some amount Δ. An equilibrium is characterized by a vector of vehicle asset values $\boldsymbol{p} = [p_0, p_1, \dots, p_A]$ and ownership costs $\boldsymbol{r} = [r_0, r_1, \dots, r_A]$ such that all markets clear.

To begin, we set new-vehicle price to be the baseline new-vehicle price plus the cost Δ associated with the regulation: $p_0 = p_{0,baseline} + \Delta$. The supplier is assumed to meet demand at this price.[28] New-vehicle demand is a function of the ownership cost vector $\boldsymbol{r}$, reflecting costs associated with all possible vehicles in the consumer's choice set. $\boldsymbol{r}$ in turn is a function of the equilibrium price vector and includes p_0 as well as used-vehicle prices (see equation [6-9] below):

$$q_0 = q_0^D(\boldsymbol{r}) = q_0^S \quad (6\text{-}7)$$

The used-vehicle market for all remaining ages $a \geq 1$ clears when:

$$q_a^D(\boldsymbol{r}) = q_a^S(q_0, \boldsymbol{p}) \quad (6\text{-}8)$$

where the expressions for q^D and q^S are as defined in Sections 6.2 and 6.3 above.

Importantly, supply and demand are written as functions of different, but closely related, vectors: In the long run, a stable vector of vehicle asset values $\boldsymbol{p}$ will directly determine a

[28] This abstracts from potential changes in market power. Extending the quantitative model to allow producers to choose a profit-maximizing price is feasible, though in the interest of reducing complexity we have abstracted from that effect here. We believe market power changes are likely to be small relative to the main effects. If large market power changes are expected under regulation, we note that they could also be approximated by adjusting Δ up or down.

corresponding vector of vehicle ownership costs $\boldsymbol{r}$ (because changes in $\boldsymbol{p}$ across ages affect depreciation as well as scrappage and repairs; see next subsection for detail). We are, therefore, left with a closed system of *A* equations (one equating supply and demand for each used-vehicle age) and *A* unknowns in the vector $\boldsymbol{p}$. This system of nonlinear equations is readily solved numerically and leads to the results presented in Section 7 for a small 1% change in purchase price. Solving the system for large values of Δ is also straightforward and provides counterfactuals that can consider how the equilibrium system evolves in regions farther away from the baseline; for larger values of Δ, the results necessarily begin to rely more heavily on the functional forms used to define demand and scrappage.

6.4.1 Asset Values and Ownership Cost

In the long run, when the vehicle stock has reached a new stable path and asset prices have stopped fluctuating, there is a straightforward relationship between $\boldsymbol{p}$ and $\boldsymbol{r}$. We describe it here, building on the setting in Jacobsen and van Benthem (2015). In the short-term transitional response to a policy, the relationship is more complex, depending on both history and expectations, and we explore that case in detail in Section 8.

In the long run, ownership cost and asset prices are related as follows:

$$r_0 = p_0 - \frac{1}{1+\delta}(1-s_1)(p_1-h_1)$$

$$r_1 = p_1 - \frac{1}{1+\delta}(1-s_2)(p_2-h_2)$$

$$\ldots$$

$$r_A = p_A \tag{6-9}$$

where δ is the discount rate, s_a is the scrappage function as above, and h_a is average per-vehicle spending on repairs at age a. Ownership cost at a particular age is the asset value at that age minus the (discounted) asset value a year later, adjusted downward for repairs and the possibility of scrap. To the extent some causes of potential scrappage can be insured against, adding the actuarially fair insurance cost instead of the scrappage possibility would lead to an equivalent ownership cost.

The role of scrappage is closely connected to the importance of tracking ownership cost *r* separately from asset values *p*. If scrap rates at older ages fall, the ownership cost at younger ages becomes implicitly smaller. For example, suppose the scrap rates of 6- through 10-year-old vehicles get smaller but the purchase price of 5-year-old vehicles stays exactly the same. Even though the price is the same, the improved life span of the 5-year-old vehicle should make it more attractive to potential buyers. The mechanism through which we capture the increased attractiveness of the vehicle is the ownership cost calculation: lower scrap rates in the future give the vehicle higher residual value and therefore lower ownership cost. The demand elasticity, operating on the ownership cost, leads to the expected increase in demand for 5-year-old vehicles in this scenario.

Because scrappage occurs when repair costs exceed the value of the vehicle, the form of the scrap function we have chosen (constant elasticity) implies the form of the underlying repair cost density. Using the implied repair cost density, we can calculate average repair costs paid (i.e., the average conditional on not scrapping) at each age h_a. No new assumptions are needed to calculate h_a; it follows using only the parameters of the scrap function (derivation in Appendix B):

$$h_a = \frac{b_a^{-1/\gamma}\gamma - b_a \gamma p_a^{1+\gamma}}{(1+\gamma)(1-b_a p_a^{\gamma})} \tag{6-10}$$

A natural feature of this setting is that repairs become an especially important component of ownership cost for the very old vehicles. Depreciation (conditional on the vehicle being in working order) becomes small in contrast. This fits with intuition and adds an important degree of realism to the setup.

6.5 Summary of Long-Run Model, Inputs, and Solution

We solve the system of equilibrium equations defined above with the key goal of translating demand elasticities and scrappage elasticities into long-run policy elasticities (i.e., the impact of a policy on equilibrium prices and quantities). The solution to the system of equations provides answers to questions like: given a regulation that increases new-vehicle cost (net of any consumer valuation placed on the changes) by an amount Δ, how much do new-vehicle sales, used-vehicle stocks, and used-vehicle asset values change once the policy's effect on the vehicle stock has stabilized?

In a setting where the good is not durable (or equivalently, where used versions are not a big part of the market), the answers to these policy questions simply echo the demand elasticities, and the model here is not needed. In the case of vehicles, asset values and scrappage impacts also enter importantly, and policy elasticities can deviate substantially from demand elasticities. We demonstrate the core intuition in Section 7.1.

All inputs needed are listed in Table 6-1. Each row contains a model parameter, its definition, and the data needed to calibrate it. The list is ordered such that each parameter can be determined using only the data described to the right, potentially combined with parameters appearing higher up in the list.

Table 6-1. Inputs Needed to Specify the Simulation Model

Parameter	Description of parameter and *data needed to calibrate*
δ	Discount rate
κ	Baseline growth rate of the vehicle stock
γ	Scrappage elasticity
b_a	Scale parameter for scrappage at each age. Calibrated using baseline vehicle prices and survival probabilities
β_a	Preference parameters determining share of spending on each vehicle age. Calibrated using baseline vehicle prices and baseline vehicle stock
$\theta_{a\hat{a}}$	Substitution among vehicles, each corresponds to an own- or cross-price vehicle demand elasticity as in equation (6-3)
θ_{Na}	Substitution between vehicles and the outside good, determined by the overall outside good elasticity and restrictions in equation (6-4)
β_N	Share of spending on the outside good. Calibrated using GDP. Note: Model output is currently independent of this parameter because income effects are all assumed to be neutral. The parameter is included to simplify demand system notation so that income effects could be more easily added.

6.6 Input Values

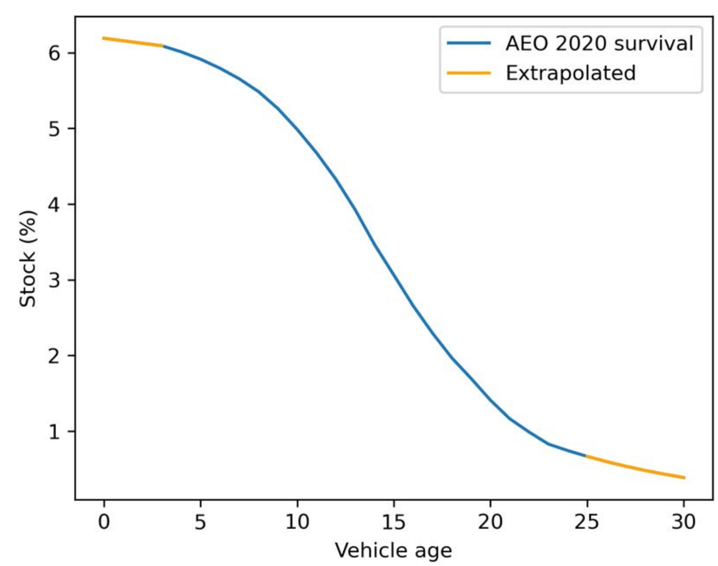
δ: We used a discount rate of 3% for all values presented in the main text. Appendix C explores alternative discount rates.

κ: We used a baseline growth rate of 0.3% per year, meant to reflect expected increases in population and vehicle demand per capita through time. Nearly all the results we present will be of policy outcomes relative to a baseline, however, so the growth rates (assumed the same in both baseline and policy cases) cancel out. Figure 9-2 is the exception, where the growth rate is visible in the levels.

γ: The scrappage elasticity is a key parameter of the model. We explored a range of values for γ taken from results in the literature: see Table 5-3 for discussion.

b_a: Equation (6-5) was then solved for b_a, and the value of b_a calibrated, so that baseline scrap rates and survival probabilities are exactly reproduced at baseline prices. We drew baseline vehicle survival probabilities (cumulative survival since new) from the Annual Energy Outlook (AEO) 2020-NEMS input files with the following two adjustments. First, we extended the survival rates for 24-year-old vehicles from AEO (the maximum age in that model) to vehicles age 25 to 30 years old in our model. This conforms with other datasets (e.g., in Leard et al. [2017]) that show a similar pattern in the oldest segment of the stock. Second, we adjusted survival of the newest vehicles so that it moves linearly between new and 3 years old (as opposed to a step function at age 3 as with AEO).[29] Figure 6-1 displays the corresponding age profile of the total inventory of vehicles. To the extent there is growth, sales and quantities at each age all grow in proportion, preserving this age profile.

Figure 6-1. Baseline Age Profile of the Vehicle Stock

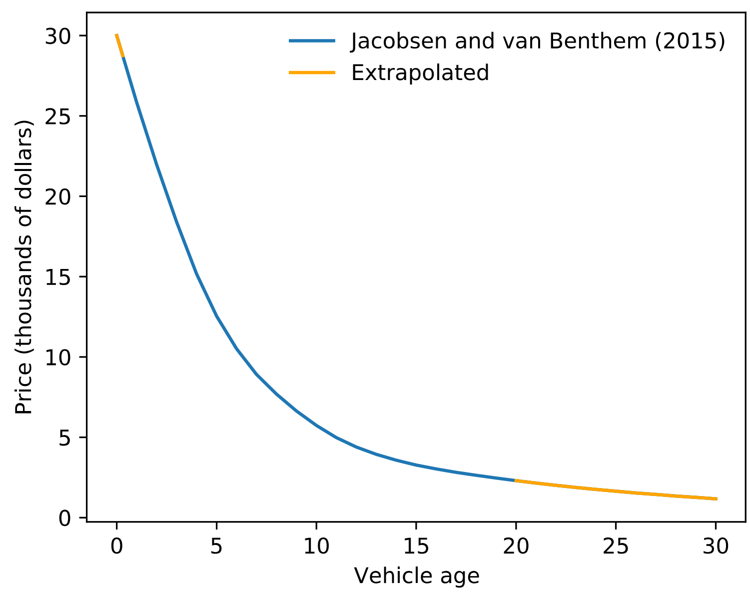


[29] This adjustment has almost no effect in practice (because survival is very close to 100% anyway) but is needed for numerical reasons (the scrappage elasticity and repair cost densities cannot be applied if baseline scrappage is exactly 0). We also think it is more realistic: even very new vehicles can be totaled (or nearly totaled) in accidents.

Our results are not sensitive to using alternative source data for the age profile, including those published in Jacobsen and van Benthem (2015) and Leard et al. (2017).

$\boldsymbol{\beta_a}$: These scale parameters in the demand system were calibrated to reproduce baseline expenditure shares at baseline prices; shares can then vary away from this level once policy is applied. Baseline shares come from combining the age profile above with data on the cost of vehicles of different ages. For our baseline vehicle costs, we used data from Table 1 of Jacobsen and van Benthem (2015) adjusted to 2020 dollars (though the units are not relevant for the elasticities). We extrapolated for prices outside the age range provided in the table.[30] This represents depreciation in typical vehicle values over their assumed 30-year lifetime in the absence of new policies or other shocks. Alternate data sources for the baseline price path show similar depreciation patterns and do not substantially affect the results. The price path we employed is shown in Figure 6-2.

Figure 6-2. Baseline Vehicle Price Profile by Age



$\theta_{a\hat{a}}, \theta_{Na}$: Demand elasticities for vehicles and the outside good are key parameters of the model. We explored a range of values taken from Tables 5-1, 5-2, and 5-4 above. New-vehicle demand elasticities range from −0.37 to −1.27 in the first panel of Table 5-1, and we explore values of

[30] Jacobsen and van Benthem provided data from age 1 to 19. The extrapolation assumed an annual depreciation rate that is constant past age 20 (at 6.5%) and the same for new vehicles as 1-year-old vehicles (at 14%).

−0.4, −0.8, and −1.27 in Section 7 below. We selected these values to span much of the range in Table 5-1. Stock et al. (2018) considered a value much closer to zero for this elasticity; we therefore also explore results from a very small new-vehicle demand elasticity (−0.1) in Appendix C.

SECTION 7.
LONG-RUN MODEL RESULTS

In this section, we present results of modeling the long-run steady-state equilibrium in the U.S. LDV market under alternative combinations of elasticity parameters. We selected combinations of parameters within ranges of elasticity estimates based on the findings of the literature synthesis presented in Section 5 to illustrate the implications of alternative assumptions.

7.1 Effects of Elasticity Parameters on Simulation Results

We first built intuition around the role of key elasticity parameters by presenting a series of illustrative cases that successively open additional channels of market adjustment.

Table 7-1 is divided into two sections. The left half shows assumptions on the elasticities of demand for vehicles and our assumption about the scrappage elasticity. The right half of the table—"Effect of a 1% increase in generalized cost"—displays what we term the "policy elasticities." We define the policy elasticity as the long-run steady-state change in any quantity (e.g., the number of new-vehicle sales) that results from a 1% increase in the generalized cost of new vehicles. The assumed increase in generalized cost is a measure of the magnitude of the policy, hence the term "policy elasticity" to represent the responsiveness to a given magnitude of policy change. For example, row 3 in Table 7-1 shows a setting with a new-vehicle price elasticity of demand set to −1. The effect of policy on new-vehicle sales in the right panel, however, is only −0.32. This section builds intuition for the much smaller effect that a policy has on vehicle sales when compared with the raw demand elasticity for new vehicles.

Table 7-1. Demonstration of Channels of Adjustment in Quantities and Prices When Generalized Cost of New Vehicles Rises by 1%

Setting				Effect of 1% Increase in Generalized Cost (Policy Elasticities)			
Vehicle Demand Elasticities				Quantities (% change)			
New-Vehicle Demand	Cross-Price New/Used	Outside Option	Scrappage Elasticity	New	Used	All	Average Age
−1.00	0.06	0	0	0.00	0.00	0.00	0.00
−1.00	0.06	−0.10	0	−0.18	−0.18	−0.18	0.00
−1.00	0.06	−0.10	−0.70	−0.32	−0.09	−0.10	0.18

7.2 Setting

The left panel displays three combinations of parameter settings, all of which have new-vehicle demand elasticities (column 1) set to −1. The choice of −1 here is for illustration and easy comparison of the relative magnitude of the demand elasticity versus the policy elasticity. Section 7.2 calibrates these elasticities to estimates from the literature.

In all three settings in the table, the cross-price elasticity between new and used vehicles is set to 0.06. That is, if the ownership cost of new vehicles rises by 1%, demand for new vehicles falls by 1%, and demand for used vehicles (summed over all ages) rises by 0.06%. Translating to derivatives, if the cost of new vehicles rises by 1%, while the cost of other vehicles remains fixed, then demand for new vehicles falls by the same number of units as the demand for used vehicles increases, and total vehicle stock stays constant.[31]

The third column shows the elasticity between all vehicles and the outside option. In the first row this is set to zero; the demand system is calibrated so that if the costs of all vehicles were to simultaneously rise by 1%, there would be no increase in demand for the outside good. In the second and third rows, this value is set to −0.1; if we were to make all vehicles 1% more expensive, aggregate demand for vehicles falls by 0.1%. Given the substitution pattern for new vehicles (all of which flows to used vehicles), it follows that the aggregate substitution to the outside good is driven by switches from used vehicles to the outside good. This pattern is helpful for intuition here but need not be the case in other calibrated scenarios.

Finally, the fourth column describing the setting shows the elasticity of scrappage. The value of 0 in the first two rows means that scrappage is exogenous: a set fraction of vehicles survive to each age regardless of vehicle values. Following AEO, that fraction is 83% to age 10 and 24% to age 20 (see Section 6.6). The elasticity of −0.7 in the third row means that if vehicle value increases by 1% at a given age, the number scrapped at that age falls by 0.7%. When the scrappage elasticity is different from 0, survival probabilities (both one-year survival, which is one minus the scrap rate, and cumulative survival to a given age) become endogenous to the policy.

To complete the setting, note that the demand system contains 30 ages, but so far we have only specified three demand elasticities. The following assumptions define the remaining

[31] This motivates the choice of 0.06 as the cross-price elasticity; a value less than 0.06 would mean that not all of the reduction in new-vehicle demand (in terms of vehicle quantities) moves to used vehicles. Some would flow to the outside good. Relative substitutability, that is, how much of the flow is to 5- versus 10- versus 20-year-old vehicles, is a function of age difference, as discussed in more detail in Appendix C.

elasticities. Own-price elasticities for used vehicles of a particular age are set the same as the new-vehicle elasticity.[32] Cross-price demand elasticities between individual ages are set to fall at 8% per year of difference in age. For a 15-year-old vehicle, for example, this translates to 47% of the total substitution going to vehicles plus or minus 3 years (so between 12 and 18) and 85% to vehicles plus or minus 8 years. Very little evidence exists in the literature on substitution across ages, so we explore a wide range of alternative assumptions in Appendix C, including cases where substitution is much more concentrated and cases where it is entirely flat across the age distribution.

7.3 Policy Impact

The right-hand panel considers the impact of a 1% increase in new-vehicle price (e.g., a tax of 1% or a regulation that raises vehicle price net of perceived fuel savings by 1%). What happens to new-vehicle sales? At first glance it might appear that we could simply apply the new-vehicle demand elasticity of −1 and conclude that the policy would reduce new-vehicle sales by 1%. However, the policy impact in the first row indicates that new-vehicle sales do not fall at all: the "policy elasticity" is zero even though the demand elasticity is set to −1.

The intuition for the zero effect in the first row is as follows: new-vehicle buyers might consider substituting toward used vehicles (or perhaps even do so in the early years of a policy), but they would soon realize that the fixed survival probabilities and reduction in new vehicles entering the system create scarcity in the used market, driving up used-vehicle prices. This spreads out the cost of the regulation across all vehicles, undoing the original motivation to substitute. The assumption of zero substitution to the outside good in this first row means that even though all ownership costs have risen, the overall demand for vehicles never falls. There is no change in either the aggregate vehicle stock or its age profile.

The second row relaxes the assumption of zero substitution to the outside good, creating a more realistic setting. The continued assumption of fixed survival probabilities (i.e., 0 scrappage elasticity) means that the ratio of new to used vehicles remains fixed. We know that all vehicle quantities must fall by the same percentage in equilibrium. As in the first row, the attempted substitution away from newer vehicles creates a price increase across all ages. Note

[32] This assumption is mainly for practicality: we know of no estimates of used-vehicle price elasticities at the individual age level. We would note that used-vehicle demand could be more elastic than new-vehicle demand because, for example, the substitutability between 10- and 11-year-old vehicles is likely greater than that between brand-new vehicles and 1-year-old vehicles. However, an argument can also be made for lower own-price elasticities for older vehicles: a would-be new vehicle buyer can substitute to an almost-new vehicle and still meet their transportation needs in a very similar way. A would-be used-vehicle buyer, on the other hand, may be considering substituting out to other modes of travel altogether. We explore both possibilities in sensitivity analysis.

that the policy elasticity (−0.18) for new-vehicle sales is still considerably smaller in magnitude than −1. This is because it is mainly the (fairly small) elasticity to the outside good that determines the decline in new-vehicle sales, not the new-vehicle demand elasticity. With fixed survival probabilities, new-vehicle sales will eventually determine the size of the whole vehicle stock, so new-vehicle sales can only fall as much as the market is willing to allow the size of the whole stock to fall.[33]

Finally, the third row introduces the full version of the model where scrappage is also allowed to fall when vehicle values rise. Here we use the scrappage elasticity estimate of −0.7 from Jacobsen and van Benthem (2015). New-vehicle sales now fall even more than in the other two cases, though the policy effect of −0.3 is still much smaller in magnitude than the demand elasticity of −1. The ability to maintain vehicles for longer, via the scrappage elasticity, means that quantity changes can now vary between vehicles of different ages. New-vehicle sales fall by 0.3%, but the overall stock only falls by 0.1%. This happens because at each age a few more vehicles of a given vintage are repaired rather than scrapped. By the time a vintage reaches age 20, the quantity has been restored almost to pre-policy levels. Long-run average vehicle age rises by 0.18% on a base of 9.6 years (average age implied by the AEO vehicle survival data discussed in Section 6.6).

7.4 Calibrated Scenarios Based on Findings of the Literature Review and Synthesis

We focused on three key input elasticities: the elasticity of demand for new vehicles, the overall substitutability between vehicles and the outside good, and the scrappage elasticity. We show how a range of different inputs along these three dimensions translates to policy elasticities over key outcomes in the vehicle stock.

The scenarios in Table 7-2 are representative of elasticities presented in the literature review in Section 5, though they do not span the whole range. (Appendix C explores cases with elasticities set at more outlying values.) New-vehicle demand elasticities in the table range from −0.4 (similar to values from Berry, Levinson, and Pakes [2004] and Leard [2021] and at the high end for long-run elasticities) to −1.3 (following the demand system in Bento et al. [2009]). Elasticities to the outside good range from 0 (no alternatives to vehicles available) to −0.14 (following the demand system in Bento et al. [2009]). We observe that in the Bento et al. (2009) demand system substitution away from new vehicles flows almost entirely to used vehicles, with

[33] The value is greater than −0.1 in magnitude because substitution to the outside good is greater at older ages than newer ages (in this stylized setting, but likely also in fact) allowing a chain of substitution that focuses on older ages.

only small effects on the total number of vehicles.[34] This is an intuitive result, so we keep it across scenarios in the table. When new vehicle elasticities are larger, the cross-price elasticity with used vehicles is also larger. We explore deviations from this in Appendix C.

The first five rows (rows A through E) hold the scrappage elasticity fixed at a value of −0.7 (Jacobsen and van Benthem [2015] and also close to the median of values in Table 5-3). The last four rows (rows F through I) explore changes in this elasticity, spanning most of the range in the literature with values of −0.2 to −1.2 (repeating scenarios B and D in terms of vehicle demand elasticities).

Table 7-2. Policy Elasticities Corresponding to Selected Demand and Scrappage Elasticities

Scenario					Effect of 1% Increase in Generalized Cost of New Vehicles (Policy Elasticities)			
	Vehicle Demand Elasticities				Quantities (% changes)			
	New-Vehicle Demand	Cross-Price New/Used	Outside Option	Scrappage Elasticity	New	Used	All	Average age
A	−0.40	0.03	0	−0.70	−0.14	0.01	0.00	0.09
B	−0.40	0.03	−0.05	−0.70	−0.17	−0.04	−0.05	0.08
C	−0.40	0.03	−0.14	−0.70	−0.23	−0.10	−0.11	0.08
D	−0.80	0.05	−0.05	−0.70	−0.25	−0.04	−0.05	0.15
E	−1.27	0.09	−0.14	−0.70	−0.39	−0.12	−0.14	0.21
F	−0.40	0.03	−0.05	−0.20	−0.14	−0.06	−0.06	0.07
G	−0.40	0.03	−0.05	−1.20	−0.19	−0.03	−0.04	0.08
H	−0.80	0.05	−0.05	−0.20	−0.19	−0.07	−0.08	0.12
I	−0.80	0.05	−0.05	−1.20	−0.27	−0.03	−0.04	0.15

Scenarios A through C explore an increase in substitution to the outside good. As we saw in Table 7-1, this is one of the most important elasticities in determining the effect of policy on new-vehicle sales. When the outside good elasticity ranges from 0 to −0.14, the new-vehicle demand elasticity of −0.4 (the same for all scenarios A through C) translates to a policy elasticity between −0.13 and −0.23.

[34] Because used vehicles are cheaper than new ones, this means that if measuring in terms of dollars the substitution is shared between used vehicles and the outside good, also an intuitive pattern.

The difference between scenarios C and D provides an interesting comparison. The effect of policy on new-vehicle sales in these two scenarios is almost the same (−0.23 versus −0.25) even though the demand elasticity for new vehicles is twice as big in scenario D as it is in scenario C (−0.8 versus −0.4). This happens because prices and effects in the used stock move very differently in the two scenarios. In Scenario C, the relatively easy substitution to the outside good means that used-vehicle prices cannot rise very much; used-vehicle buyers would rather switch to the outside good than pay higher prices. Much of the cost of the policy, therefore, falls on new vehicle buyers. In Scenario D, there is less flexibility to go to an outside good, so used-vehicle values rise more sharply. The higher values in the used market do two things: First, they mean that residual values are better for new-vehicle buyers, and the cost of the policy does not fall as much on new-vehicle buyers. Second, higher values in the used market also reduce scrappage, so the used (and overall) stocks shrink by relatively little in Scenario D. Average age also increases much more sharply in Scenario D than in Scenario C, rising by 0.15% for a 1% increase in generalized cost of new vehicles.

The greatest impact on the vehicle stock occurs in Scenario E in the table: in this scenario new-vehicle demand is set at its most elastic and substitution to the outside good is also set at its most elastic. The elasticities used in Scenario E follow the demand system estimated in Bento et al. (2009).

Next, we consider the effect of the scrappage elasticity. First note that in all rows in the table the used stock shrinks by less (in absolute value) than new-vehicle sales shrink; costlier new vehicles are leading to longer vehicle lifetimes. This implies some "leakage" of gasoline savings compared with a world where the whole stock shrinks by the same amount as new-vehicle sales, as identified in Jacobsen and van Benthem (2015). In theory, the presence of a scrappage effect could mean that the used stock actually grows larger as the result of policy (as opposed to just shrinking less). We note, however, that this happens in only a single scenario in Table 7-2: in Scenario A when there is no substitution available to an outside good. Even very small elasticities to the outside good (e.g., −0.05) are sufficient to mean the used stock shrinks.

The second panel (Scenarios F through I) of Table 7-2 shows how the policy elasticities depend on the scrappage elasticity. Between rows F and G, for example, the effect on the stock is 50% larger (−0.06 versus −0.04) when the scrap elasticity is −0.2 versus −1.2. This is intuitive: when there is less room for a scrappage effect to operate (e.g., elasticity −0.2) used vehicles will "make up" less of the loss in new-vehicle sales, so the effect on total stock is larger. In rows H and I, when new-vehicle demand is more elastic, the scrappage elasticity is also somewhat more important.

Table 7-3 displays additional policy elasticities for the same nine scenarios, now focusing on prices and scrappage. Asset values (in the generalized sense used throughout) are shown in the first group of columns. For relatively young vehicles, asset values rise substantially (would-be new-vehicle buyers want to substitute into the used market, for example, by holding onto a vehicle until it is 5 years old instead of trading it in at 4). The increase in asset value for age-5 vehicles, for example, reduces the scrappage rate for these vehicles shown in the next group of columns. This "produces" extra used vehicles in the middle of the age range, helping consumers make up for the new vehicles lost to reduced sales. This could perhaps be the end of the story, with the market for very old vehicles remaining relatively isolated from the policy. However, notice that the extra middle-aged vehicles created by the scrappage effect just mentioned could, if they continue to be maintained, eventually become 25-year-old vehicles. This creates a potential surplus of 25-year-old vehicles because demand for them has not increased by much.[35] Equilibrium asset prices for the oldest vehicles must, therefore, fall to increase scrappage and prevent the surplus.

Table 7-3. Additional Policy Elasticities Corresponding to Selected Demand and Scrappage Elasticities

	Effect of 1% Increase in Generalized Cost of New Vehicles (Policy Elasticities)							
	Asset Value (generalized price)			Scrappage Rate		5-Year Depreciation		
Scenario	**Age 1**	**Age 5**	**Age 25**	**Age 5**	**Age 25**	**New**	**Age 5**	**Age 20**
A	1.03	1.14	−0.13	−0.79	0.09	0.88	1.05	0.01
B	1.02	1.09	−0.10	−0.76	0.07	0.90	1.00	0.02
C	0.99	1.01	−0.05	−0.70	0.04	0.94	0.93	0.03
D	1.04	1.24	−0.10	−0.86	0.07	0.82	1.05	0.14
E	1.04	1.28	0.04	−0.89	−0.03	0.80	1.04	0.29
F	1.03	1.24	0.31	−0.25	−0.06	0.87	1.19	0.66
G	1.01	1.00	−0.05	−1.19	0.06	0.82	0.77	−0.01
H	1.06	1.38	1.13	−0.27	−0.22	0.79	1.22	1.33
I	1.03	1.17	−0.11	−1.38	0.13	0.75	0.83	0.00

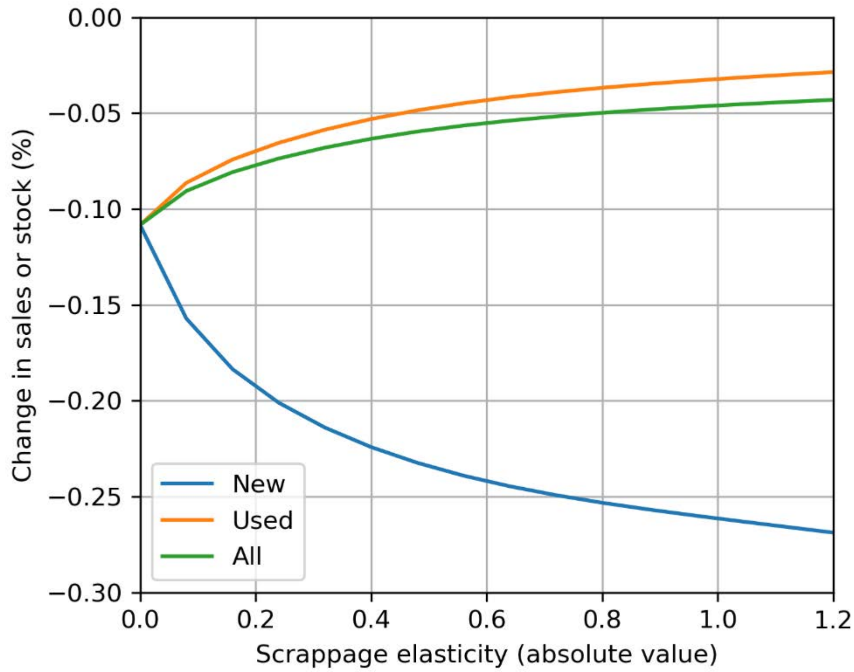
The effect of the policy on 5-year depreciation costs (last group of columns) is generally to increase them: this must be the case at least on average over the vehicle life because the initial purchase price has risen, and we assumed the vehicle is fully depreciated by age 30. The pattern

[35] The strength of this effect is determined by the demand system in equilibrium: if there is not much substitution between new vehicles and 25-year-old ones (our baseline assumption), then policy will not increase demand for 25-year-old vehicles very much above the baseline.

in asset prices discussed above, however, means that changes in depreciation will not be uniform; it is not the case that depreciation simply rises by 1% at every age. In particular, the core substitution pattern (reduced new-vehicle sales increase demand for relatively new substitutes) increases asset values for 5-year-old vehicles by more than 1%. Depreciation in the first 5 years, therefore, rises by less than 1%. Asset values fall more quickly going into middle age (as above, to prevent surplus at the oldest ages), leading to depreciation costs often exceeding a 1% increase for vehicles aging from 5 to 10 years old. Finally, depreciation for 20-year-old vehicles tends to rise only a small amount in response to the policy or even fall, again due to the pattern in asset values. Changes in the scrappage elasticity produce significant changes in this pattern: for example, when scrappage elasticities are chosen to be small (Scenarios F and H), then asset values and depreciation for older vehicles rises because the “surplus” effect from reduced scrappage among middle-aged vehicles is less pronounced. Conversely, when scrappage elasticities are chosen to be very large, then depreciation for older vehicles changes very little and can even shrink slightly as in the case of Scenario G.

Figure 7-1 displays the divergence in effects on new-vehicle sales and the used stock for a continuum of scrappage elasticities between 0 (fixed vehicle survival probabilities) and −1.2 (among the most elastic responses estimated in the literature). In the figure, vehicle demand elasticities are fixed as in Scenario D of Table 7-2. (Appendix C repeats the figure for Scenarios B and E.) When the scrap elasticity is −0.7 on the horizontal axis, the values on the vertical axis reflect the policy elasticities as shown in Table 7-2 for Scenario D. Even for the most elastic scrappage in the figure, the policy elasticity for new-vehicle sales is still much lower in magnitude than the new-vehicle demand elasticity of −0.8. Effects on the vehicle stock overall rise toward zero as scrappage effects grow large. Large scrap elasticities mean that it is cheap to prolong vehicle life, so substitution to the outside good becomes a less important feature of the equilibrium.

Figure 7-1. Policy Effect on LDV Stocks as a Function of the Scrappage Elasticity for a 1% Increase in Generalized Cost of New Vehicles, Scenario D



Note: The new-vehicle demand elasticity for Scenario D is −0.8. This figure demonstrates that the policy elasticity (shown on the vertical axis) is much less elastic than the demand elasticity for a plausible range of scrappage elasticities.

7.5 Effects by Vehicle Age

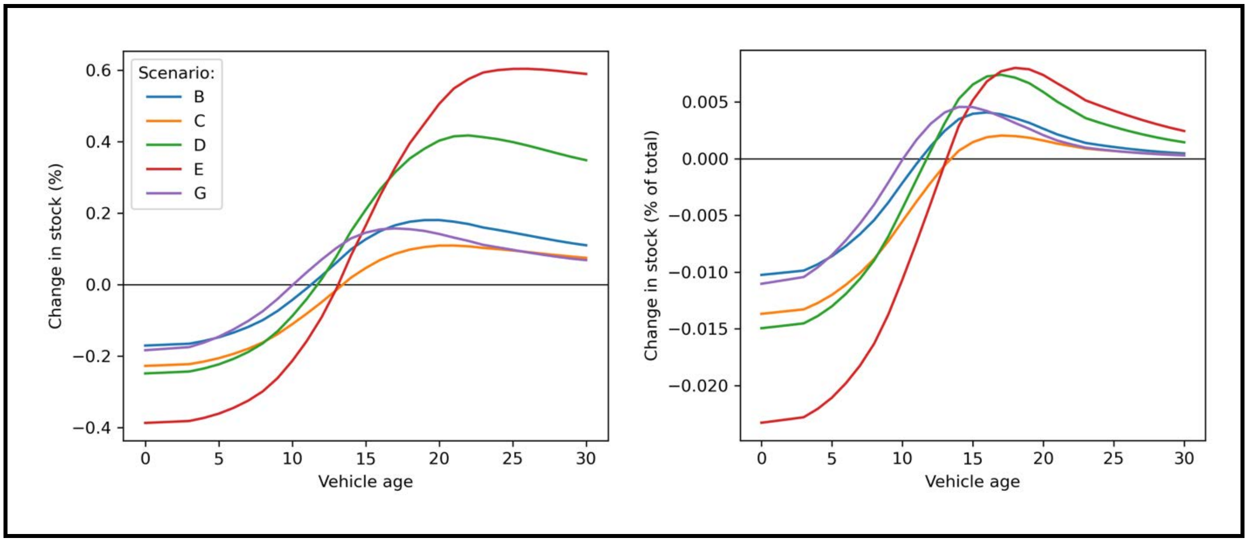
Figure 7-2 displays changes in the age profile of the vehicle stock as a result of policy. All changes shown are for a 1% increase in generalized cost, so these values can again be interpreted as policy elasticities. The left panel shows changes relative to the no-policy case, by age; the right panel shows the change at each age relative to the aggregate baseline stock.

The policy elasticities for new vehicles can be read off the vertical intercepts of the left panel of the figure: for example, for Scenario D in Table 7-2 the policy elasticity for new vehicles is −0.25, so the vertical intercept in the left panel is −0.25.

Quantities of vehicles over 15 years old increase in all the scenarios shown. Because these vehicles are a relatively small share of the overall stock, the change in used vehicles as a whole (i.e., age 1 through 30) is negative. This is more easily seen in the right-hand panel, which shows the changes as a fraction of the stock (rather than as a fraction of the baseline).

The right panel is useful for considering the age profile in the broader context. Notice, for example, that when the scrappage elasticity is large (Scenario G in purple), the bump up in quantities for middle-aged vehicles is larger and occurs at a younger age relative to Scenario B in blue because the greater elasticity means relatively more young vehicles can be saved from scrappage. Once younger vehicles are saved (replacing some of the lost new-vehicle sales), relatively less saving of the oldest vehicles occurs (the purple line is slightly under the blue line for age 20, for example). The integral of the right-hand panel reflects the policy elasticity for the total inventory as reflected in Table 7-2 above; for example, the blue line for Scenario B integrates to −0.04.

Figure 7-2. Changes in Long-Run Vehicle Inventory by Vehicle Age



7.6 Summary

The long-run results generate policy elasticities for new-vehicle sales that are substantially smaller than new-vehicle demand elasticities. This effect is strongest when scrappage is inelastic or when there is little substitution to the outside good. Intuitively, these two conditions are also the ones where used-vehicle prices will rise the most in equilibrium. If scrappage is inelastic, shortages in the used market are persistent and cannot be alleviated by supply, so prices rise. Similarly, if used-vehicle owners are unwilling to substitute away to an outside good, then there are more serious shortages in the used market, leading to higher prices.

We also observe that the increase in average age of vehicles tends to be small; reductions in scrappage rates for newer used vehicles increase quantities in the middle of the age distribution. There is not much upward pressure on the prices of the very oldest vehicles (because they are not very good substitutes for new vehicles), so there is not much increase in their quantity.

SECTION 8.
DYNAMIC TRANSITION PATH MODELING

When new policy is introduced or an existing policy is changed, the vehicle stock will not instantaneously move to its new long-run steady state described in Section 6. Instead, it will evolve dynamically, only arriving at the new steady state after a period of years or decades. In the early years of a policy, for example, unregulated and partially regulated vintages will still exist within the stock. Prices and scrappage of these older vehicles are driven by expectations, preferences, and the rate at which newly regulated vehicles are entering the system.

An important advance over existing models of the vehicle stock is our focus on dynamics and consideration of the way expectations enter the used-vehicle market. Existing models that address the used market are scarce, and many either ignore the dynamics or have difficult-to-interpret reduced forms and can produce inconsistent results. The simulation of the used-vehicle market in Jacobsen and van Benthem (2015) is most like the setup here. In that model, price expectations are included, though assumed to be myopic: consumers expect the age profile of vehicle values next year to be the same as the profile this year.[36] Here we are able to capture the decisions of more sophisticated agents who can anticipate changes in vehicle markets caused by changes in current policy. This provides several advantages, including theoretically consistent time paths, improved ability to conduct welfare analysis, and greater realism (at least to the degree real markets tend to evolve rationally). The model here is also capable of simulating transition paths under many different forms of myopic expectations.

The focus of the setup below is specifically on the dynamics and transition path: some resolution is given up (e.g., in aggregating across vehicle models and classes), but in exchange the model provides an intuitive and utility-consistent view of the way the age structure of the vehicle stock evolves with policy. To the extent that disaggregated outputs are needed for specific analyses, this model could potentially be linked with more disaggregated models of the transportation sector to estimate detailed impacts consistent with the aggregate market outcomes.

8.1 Additional Notation

We build on the notation used in Section 6 to evaluate the long-run policy outcome, now adding a subscript t (for year) throughout. Specifically:

$q_{a,t}$ number of vehicles of age a present in year t, so $\sum_a q_{a,t}$ is the total vehicle stock in year t

[36] For example: "The value of my 5-year-old vehicle next year will equal the value of a 6-year-old vehicle today."

$s_{a,t}, h_{a,t}, p_{a,t}, r_{a,t}$

time paths of scrappage, repair spending, asset values, and ownership cost analogous to the steady-state values in Section 6.

8.2 Demand and Supply

The vehicle demand system is the same as that presented in Section 6 and provides a flexible yet parsimonious structure. It allows us to easily explore arbitrary demand elasticities in a utility-consistent way. In the dynamic setting, demand in any given time period t is given by equation (8-1) with preference parameters β_a and $\theta_{a\hat{a}}$ as described above. Subscripts t now appear on prices, quantities, and income.

$$q_{a,t}^{D}(\boldsymbol{r_t}) = \frac{M_t}{r_{a,t}}\left(\beta_a + \sum_{\hat{a}=0}^{A} \theta_{a\hat{a}} \ln\left(r_{\hat{a},t}\right)\right) \tag{8-1}$$

Income M_t scales demand equally across ages and increases over time at rate κ: $M_{t+1} = (1+\kappa)M_t \ \forall \ t$. κ is chosen to reflect projected growth in the vehicle stock over time. The age profile is assumed to remain stable in the baseline. Without a policy change, new-vehicle sales as well as the entire vehicle inventory, grow steadily at the rate κ.[37] After a policy is added and the transition to the new long-run equilibrium is complete, the inventory will again resume steady growth at rate κ. The growth path will be lower to the extent the regulation was costly and caused switching to the outside good on an aggregate level.

Vehicle supply each year t is a function of the incoming stock from the previous year adjusted for scrappage (following equations [6-5] and [6-6]). Note that supply now depends on equilibrium quantities from a year ago and becomes part of the dynamic path:

$$q_{a,t}^{S} = \left(1 - b_a\left(p_{a,t}\right)^{\gamma}\right) q_{a-1,t-1} \tag{8-2}$$

8.3 Asset Values and Ownership Cost

In considering the connection between asset values and ownership cost, the long-run version of the model in Section 6 makes use of the steady-state assumption. Specifically, it uses the feature that the scrappage and depreciation rate of vehicles is stable in the long run. If new

[37] Without a policy change, scrap rates and vehicle lifetimes are assumed to be steady so that growth in new-vehicle sales translates to growth in the whole stock over time. Somewhat more realism could be attained by introducing technological change that improves vehicle reliability over time. This complicates the model considerably, however, and we believe it would scale the baseline and policy cases nearly proportionally and not contribute significantly to the findings.

vehicles have tended to lose 40% of their value in the first 3 years, then a new vehicle purchased this year can be expected to behave the same way.

When a policy is introduced, this is no longer the case. For example, if a policy reduces new-vehicle sales, then we can reasonably expect that used vehicles will become a little scarcer and, therefore more valuable, a few years from now. Expected depreciation is, therefore, less than 40%. A forward-looking, rational agent will correctly anticipate this type of change and can make an informed decision about a new LDV purchase at any point along the transition path. A myopic agent, on the other hand, might under- or overcorrect for the effect the policy is having and make a mistake in their decision. We focus on the forward-looking (and, therefore, utility-maximizing) case in our main analysis. The model can also apply myopic expectations of any particular form; we explore a myopic case in Appendix D and show how it converges to the same steady state, but along a different transition path in the short run.

Rational expectations is a typical assumption in dynamic modeling and provides valuable insights into how markets may respond to changing expectations even before a policy or other change takes place. As soon as a policy change is announced, markets will respond to the anticipated impacts of that policy, even well before the policy goes into effect. For instance, there is empirical evidence of increased buying in advance of regulatory changes going into effect, once those changes have been announced (e.g., Ciccone, 2018; Coglianese et al., 2016). Although individuals may not be well-informed about coming policies and the potential impacts on new- and used-vehicle prices, sophisticated market actors such as leasing companies and banks have strong incentives to follow policy developments and analyze potential impacts. These market actors will adjust the terms of the products they offer consumers to reflect changes such as updated residual values for vehicles, which is expected to lead to efficient market adjustments in anticipation of regulatory or other anticipated changes.[38]

Expectations enter the model where we consider the relationship between asset values and ownership cost. Equation (9) above expands to:

[38] Of course, there are also cases where individual consumers miscalculate the potential costs and benefits of their own choices, such as potentially underestimating the benefits of fuel economy, and markets do not necessarily lead to efficient reflection of these costs and benefits.

$$E_t[r_{0,t}] = p_{0,t} - \frac{1}{1+\delta} E_t\left[(1 - s_{1,t+1})(p_{1,t+1} - h_{1,t+1})\right]$$

$$E_t[r_{1,t}] = p_{1,t} - \frac{1}{1+\delta} E_t\left[(1 - s_{2,t+1})(p_{2,t+1} - h_{2,t+1})\right]$$

$$\ldots$$

$$E_t[r_{A,t}] = r_{A,t} = p_{A,t} \tag{8-3}$$

where $E_t[\cdot]$ refers to the expectation held at time t about the object in square brackets. In equation (8-3), the expected 1-year ownership cost of a new vehicle, for example, is its new vehicle price less its residual value (the expected value of a 1-year-old vehicle next year, net of scrap and repair). The agent makes decisions about vehicles in time t based on expected ownership cost. When agents have rational, forward-looking expectations, we will have that $E_t\left[p_{a,t+1}\right] = p_{a,t+1}\ \forall\ a, t$ and the dynamic path produced by the model maximizes utility in any given time period. It also maximizes present discounted utility across time periods: the agent in the present makes purchase and repair choices based on the true future residual value, which in turn reflects future willingness to pay for a used version of the vehicle.

8.4 Dynamic Market Equilibrium

For ease of notation, we first observe that demand at time t, expressed in equation (8-1) as a function of $\boldsymbol{r_t}$, can be rewritten as a function of $\boldsymbol{p_t}$ and $E_t[\boldsymbol{p_{t+1}}]$ by using equation (8-3). Bold type indicates the vector across ages as before.

An equilibrium over a finite horizon T is defined as a set of vectors $\boldsymbol{p_t}$, for t between 1 and T, such that the following conditions hold:

i) New-vehicle quantity in each time period is given by demand (assuming elastic supply as before):

$$q_{0,t} = q_{0,t}^{D}(\boldsymbol{p_t}, E_t[\boldsymbol{p_{t+1}}]) \tag{8-4}$$

ii) Used-vehicle quantities for all $a \geq 1$ are such that demand and supply are equated at each time t:

$$q_{a,t}^{D}(\boldsymbol{p_t}, E_t[\boldsymbol{p_{t+1}}]) = q_{a,t}^{S}\left(q_{a-1,t-1}, \boldsymbol{p_t}\right) \tag{8-5}$$

where $q_{a,0}$ (the incoming vehicle stock from the before the policy is implemented) is given by the long-run equilibrium from Section 6 when Δ=0, that is, the steady state is in place before the policy change. The model is, therefore, constructed such that time $t = 1$ is defined as the announcement date of the policy. The implementation of the policy on new vehicles could also begin immediately in time 1, but this is not necessary. To the extent implementation (or additional phase-in) occurs when $t > 1$, another advantage of a dynamic model is that anticipation effects (e.g., "prebuying") can be measured.

iii) Expectations are such that:

$$E_t[\boldsymbol{p_{t+1}}] = \boldsymbol{p_{t+1}} \;\forall\, t \;\in [0, T-1]$$

$$E_T[\boldsymbol{p_{T+1}}] = \boldsymbol{p} \tag{8-6}$$

where $\boldsymbol{p}$ without subscript is the long-run policy outcome computed in Section 6. Expectations in all time periods 1 through $T - 1$ are rational. The assumption on expectations at T is made for computational convenience and discussed below.

8.5 Computation

We use the following algorithm to find a series of price vectors that satisfy all of equations (8-4) through (8-6) above.[39] The equilibrium quantities and scrap rates follow from the price vectors:

1) Set the starting value of expectations for time periods 1 through $T - 1$ equal to the baseline price vector (or the policy price vector, either appears to converge about equally quickly).

2) Solve for the individual time period equilibria from $t = 1$ to T sequentially (because supply at time t depends on quantities from $t - 1$).

3) Use the results from Step (2) to assign a new set of expectations for time periods 1 through $T - 1$.[40]

4) Iterate Steps (2) and (3) to a fixed point.

Step (2) ensures that equations (14) and (15) hold given expectations. Step (4) ensures that equation (16) holds.[41] In all reported runs, we selected a value of T sufficiently large that the

[39] Although we cannot completely rule out the possibility that multiple time paths might satisfy all the conditions, we have also never encountered multiple equilibria over (very) many different model runs and starting values. We would also note that the dynamic solutions we report evolve smoothly from the baseline steady state to the policy steady state, both of which are uniquely determined.

[40] Convergence is faster in some cases if using a scaling factor (i.e., moving 0.9 times the distance between the values for expectations and the outcome price vectors from the last iteration). The final solution is unaffected.

[41] We use the Python SciPy "optimize" library for numerical solution.

price vector at time $T - 1$ has already converged nearly (to a machine epsilon) to the long-run steady state. 100 years is (much) more than sufficient for this in all scenarios explored; the majority of transition dynamics are complete by $t = 20$.

SECTION 9.
RESULTS OF DYNAMIC TRANSITION PATH SIMULATIONS

We computed the results of a dynamic transition following the setup above. The paths explored below all reflect the results of computations done under Scenario D from Table 7-2 above. This scenario is used as an example to show how the vehicle stock evolves through time. The same figures under the assumptions of Scenario B are produced in Appendix D. The scale of effects differs, but the patterns and intuition for the transition path are very similar.

9.1 Vehicle Market Dynamics under Rational Expectations

Figure 9-1 displays the time path of the effect of policy (a 1% increase in generalized cost as before) on new-vehicle sales. The horizontal dashed line shows the long-run effect: −0.25% as reported in Table 7-2 for Scenario D. The goal here is to study the path that new-vehicle sales take through time. The top-left panel shows an "immediate" policy: in time 0, the policy is announced and fully implemented. There is no change leading up to time 0 (because the policy is not announced yet) and then a drop in sales at time 0 of about 0.4%. Sales then recover and after about 5 years settle in at their long-run steady state value of 0.25% less than baseline. The reason for the larger sales drop at the beginning is that shortages have not yet appeared in the used market: would-be new-vehicle buyers can simply hold on to their existing used vehicle. We note that the demand elasticity is –0.8, yet the sales drop at time 0 is only 0.4% because price effects in the used market, unlike quantity effects, happen immediately. Consumers expect that future used prices will be higher, making current used prices higher in anticipation, leading to an effect on sales that is smaller than the demand elasticity. Although we do not model dealerships separately from the representative agent, in more practical terms, the likely channel is that dealers will understand the changes coming in the used market and offer higher trade-in values to new-vehicle buyers. From the perspective of a new-vehicle buyer, the 1% policy effect is then muted because they are also receiving a better trade-in price for their used vehicle.

The top-right panel considers the same policy, going into effect all at once at time 0, but now it is preannounced. Even though nothing has changed in the new-vehicle market at time –5 (that is, 5 years before the policy goes into effect), there are already some visible effects. In particular, the announcement of the policy is a windfall gain to used-vehicle owners: asset values rise in anticipation of shortages that will occur several years in the future. This is a small-scale version of changes in real estate prices that can occur even when the announced change is decades away. As pointed out by a reviewer, Holland, Mansur, and Yates (forthcoming) also found substantial responses in vehicle markets in anticipation of policy changes when using a dynamic model. In one of their scenarios, they assessed a scenario incorporating a future ban on gasoline vehicle production, which leads to a spike in production of these vehicles before the ban goes into effect (leading the authors to explore alternative policies that could increase economic efficiency relative to a production ban). The expected lifetime of the asset is what determines how far out policy can matter. For vehicles in this model, this seems to be a little over 5 years. The higher used-vehicle values (and anticipation of even better trade-in values coming later, when a current new-vehicle buyer might be thinking about trading in) make new-vehicle purchases ever more attractive leading up to time 0. At time 0, the impact of the policy on new-vehicle sales is now even greater than in the top-left case: when there is preannouncement, the market prepares by building up the vehicle stock ahead, allowing it to avoid even more purchases once the policy enters. Preannouncement has no effect on the long-run outcome: new vehicle sales converge to the 0.25% decline in a little over 5 years.

The lower left panel considers a policy that is phased in over 5 years, with the policy announced in time 0 together with the first piece of the phase-in. The time 0 effect consists of two countervailing forces. First, there is the impact of the policy that will tend to reduce new-vehicle sales. Second is the impact of the announced trajectory, encouraging new-vehicle buyers to purchase now (i.e., in time 0) before the policy becomes stronger. In this particular case, the positive effect on sales slightly outweighs the negative, so, on net, sales increase in time 0. In years 1 through 5, sales decline steadily as the policy phases in. In year 6 and beyond, once the policy is fully in place, sales recover toward the same long-run outcome as before. The phase-in delays convergence to the long-run steady state, which now occurs around time period 10.

Finally, the lower right panel combines phase-in with preannouncement, likely the most realistic setting. Some prebuying occurs (though relatively little, because the phase-in dilutes the benefits over time), and convergence to the steady state occurs after about 10 years. To the extent the phase-in of a policy is made smoother (e.g., by placing only a slight change in year 0 and then accelerating in the later years of phase-in), the transition effect will be correspondingly smoother.

Figure 9-1. Dynamics of New-Vehicle Sales under Alternative Policy Implementation Scenarios

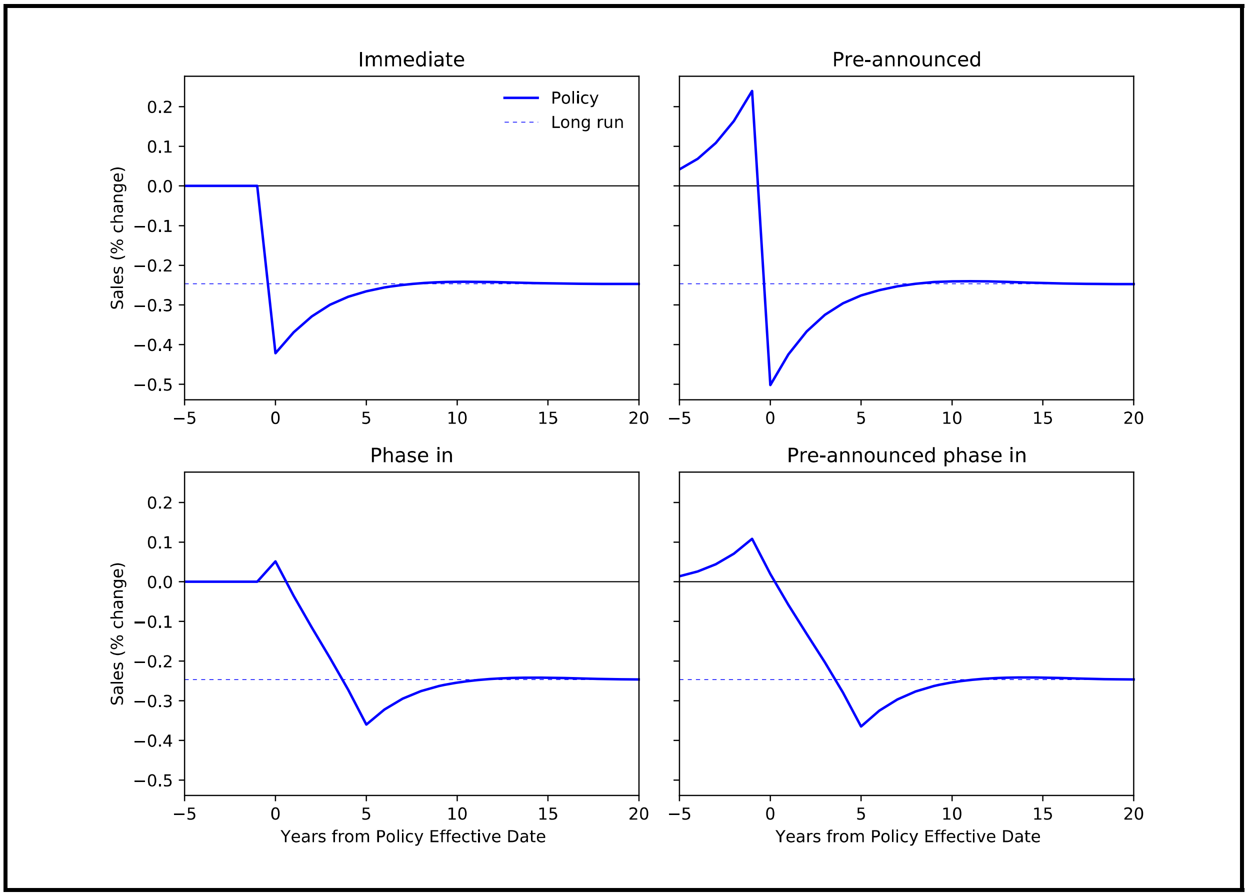


Figure 9-2 presents the same data from the top-left and bottom-right panels in Figure 9-1, but now in levels, with the no-policy baseline equal to 100. The background trend upward in new-vehicle sales dominates in the case of the preannounced phase-in: the policy does not initially reduce vehicle sales in an absolute sense but instead slows the growth in vehicle sales during the phase-in period. A stronger policy, even if phased in, could reduce vehicle sales in an absolute sense while it phases in. In either case, once the new steady state is reached growth in the new vehicle market will resume (driven here by an assumed exogenous, steady increase in the population, or per capita demand for vehicle travel).

Figure 9-2. Dynamics of New-Vehicle Sales (Levels), Baseline = 100

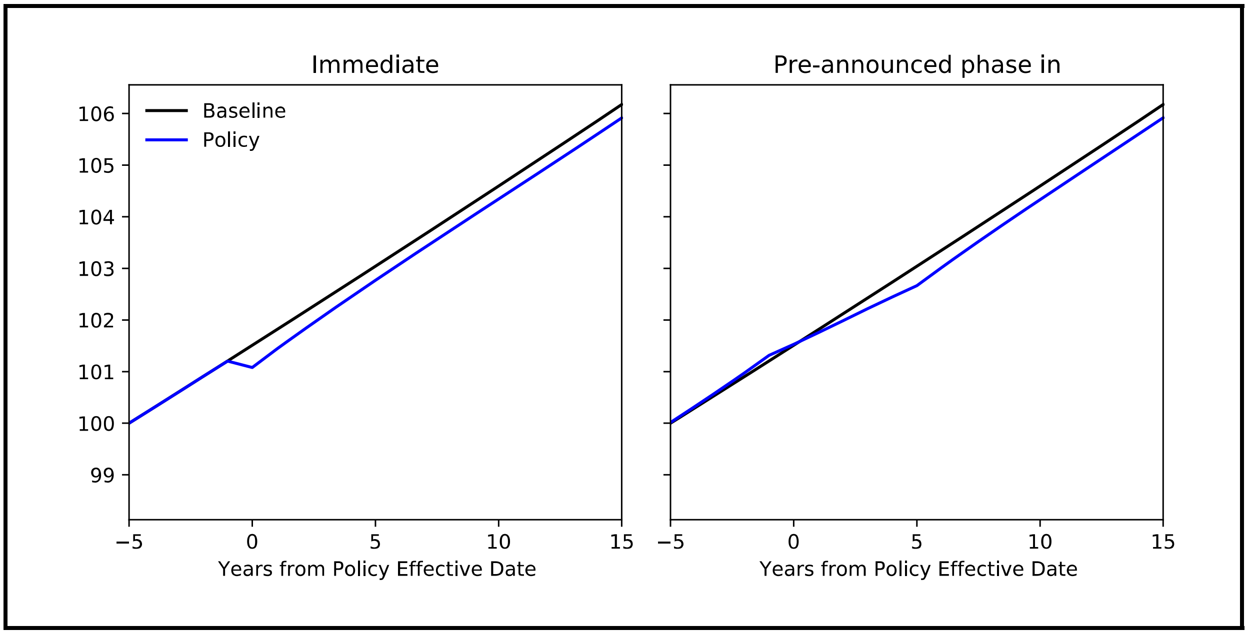
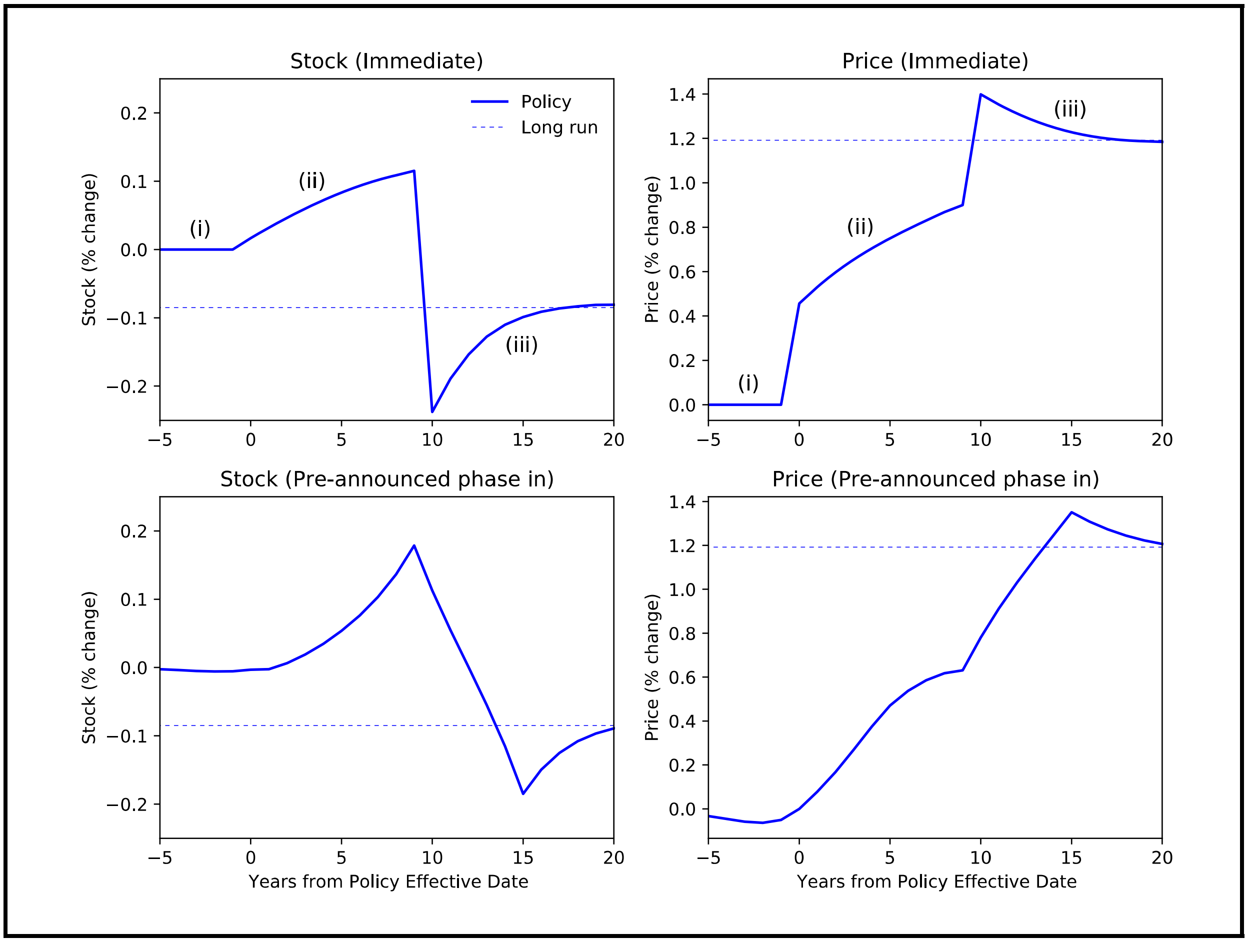


Figure 9-3 explores effects in the used-vehicle stock, picking out a single age to provide intuition. The figure follows the stocks and prices of 10-year-old vehicles through time. In the top left, we see three distinct phases of the impact on the stock of 10-year-old vehicles. Because there is no preannouncement in the top left, Phase (i) is flat, reflecting the baseline. At time period 0, the policy starts to raise used-vehicle prices, slowing scrappage of all vintages. As Phase (ii) continues, the effect from reduced scrappage compounds: in time period 1, the scrappage effect has only operated for 1 year, but by time period 9, there have been 9 years' worth of scrappage effects accumulated into the vintage that is 10 years old in year 9. Time period 9, therefore, sees the maximum quantity of age-10 vehicles.

In time period 10, the first vintage that was directly affected by the policy (vehicles that were brand new in time period 0 of Figure 9-1) turns 10 years old. The original shock to new-vehicle sales shows up in the big drop in Figure 9-3 for time period 10. The shock to new-vehicle sales in year 0 was –0.4%, but the shock visible in Figure 9-3 is only a little over –0.2%. The reason the shock has gotten smaller over time is again the reduced scrappage. Roughly half of the decline in sales when the vehicles were new has been made up by the time they reach age 10. Finally, Phase (iii) in the top-left graph just mirrors the recovery in new-vehicle sales that we saw in Figure 9-1.

Figure 9-3. Dynamics of the Used-Vehicle Inventory under Alternative Policy Implementation Scenarios: Age 10 Vehicles



The top right of Figure 9-3 follows prices. Note that the price jumps up discontinuously in time period 0: this reflects the capitalization of the policy announcement. The continued increase in price during Phase (ii) marked on the price graph comes from ever-increasing shortages as the policy continues. Not only do the shortages increase, the vintages of vehicles experiencing those shortages also get "closer" to age 10. By time period 9, for example, there is a shortage of 9-year-old vehicles (caused by the initial drop in sales 9 years earlier), and because 10-year-old vehicles could be quite good substitutes for 9-year-old ones, the price effects grow stronger. At time period 10, the discontinuity from sales is visible in prices. Now, not only are close substitutes in short supply, 10-year-old vehicles themselves are in short supply. From there, prices move downward toward the steady state as new-vehicle sales (10 years ago) recover.

The bottom two graphics show the same effects, but now with the effects of preannouncement and phase-in. Preannouncement appears as a slight drop in prices and quantities of 10-year-old vehicles at the time of preannouncement (they are driven out of the stock by the surplus of vehicles coming in as new). The 5-year phase-in period replaces the sharp jumps between Phases (ii) and (iii) in the top panels. Finally, the recovery toward steady state in Phase (iii) is very similar to the top panels.

Applying the intuition from a single age of vehicle, we now examine the stock of vehicles as a whole in response to a policy announced 5 years before its effective date and then phased in over five years. Figure 9-4 divides the stock into three parts with roughly equal stocks in the baseline: new through 5-year-old vehicles, 6- through 11-year-old vehicles, and 12 through 30-year-old vehicles. The changes in these stocks are followed through time, as well as the change in the total vehicle inventory labeled “All” in the blue dashed line.

The inventory as a whole moves smoothly, increasing slightly in the years leading up to the policy (prebuying effects) and then declining smoothly to its steady state reduction of 0.05% (as in Table 7-2). The three components move much more dynamically, following the patterns described above. Newer vehicle stocks, in purple, decline fairly sharply as the policy phases in and then recover to their steady state once the preexisting used stock can no longer buffer the initial decline in sales. Middle-aged vehicles in orange follow the pattern for 10-year-old vehicles described just above. There is an initial surge because scrappage is reduced and the initial stocks of the middle-aged vehicles were sold before the policy was put in place. Then, once enough time has passed that the policy affected the original sales of middle-aged vehicles, their quantities decline and settle at the steady state. The oldest vehicles follow the same general pattern, with two notable differences. First, the “increasing” phase can last much longer because the oldest vehicles were originally sold a long time before policy came into effect. Second, these vehicles can settle at a steady state above the baseline because the scrappage effects get to compound over a long horizon. Twenty years of compounded reductions in scrappage amount to a long-run increase in quantities of 0.24% for the oldest vehicles, even though the original sales of those vintages are about 0.25% smaller than the baseline.

Figure 9-4. Dynamics in the Used-Vehicle Market with a Preannounced, Phased-In Policy: Inventory Changes by Vehicle Age Group

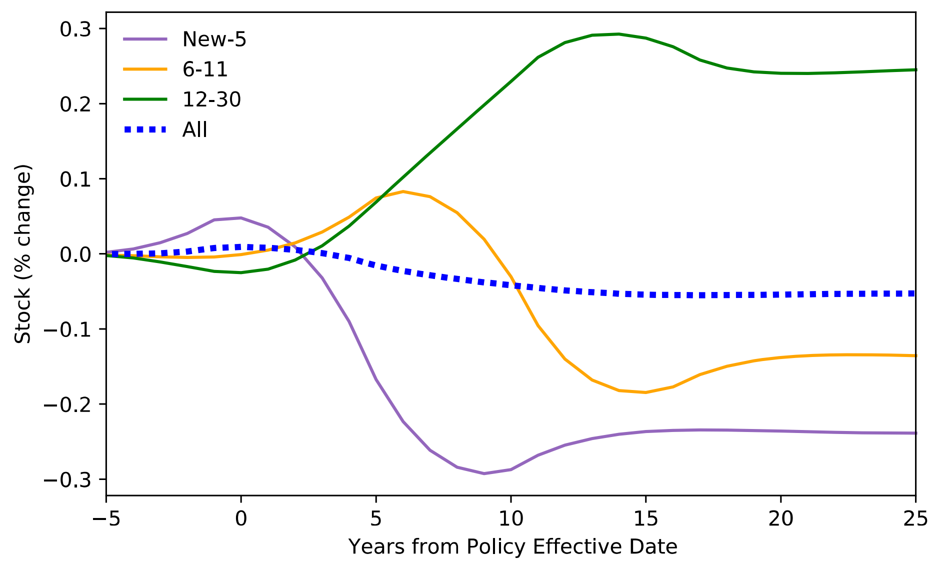
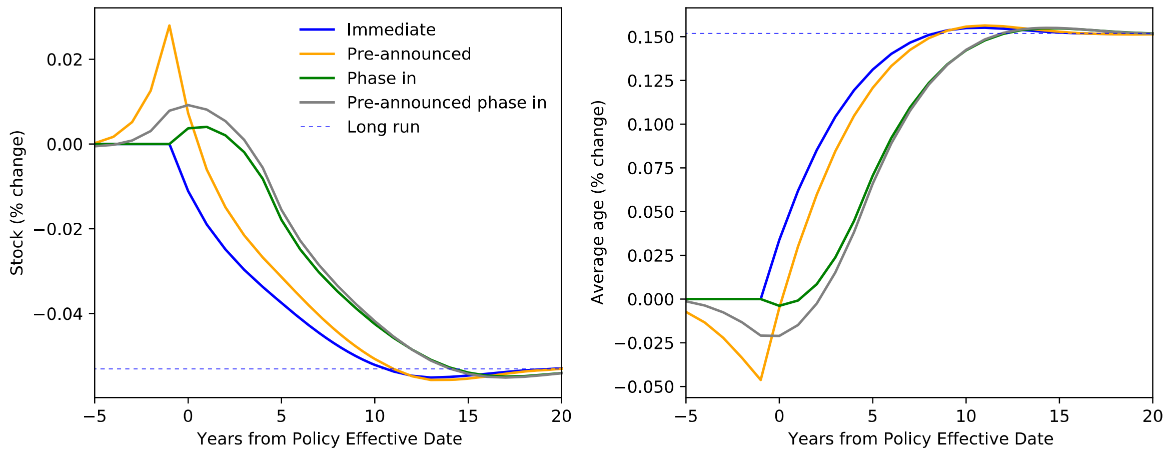


Figure 9-5 compares the patterns in overall inventory and average age for the four policy approaches in terms of preannouncement and phase-in. The gray line in the left panel is the same as the dashed blue line in Figure 9-4 above (the scale on the vertical axis is expanded).

The right-hand panel of the figure shows average age through time. For the most part, average age moves inversely to the total inventory: when there is prebuying, we see average age fall for a brief period, for example. Average age increases by a relatively small amount in the long run, by 0.15% for a 1% generalized cost increase, and converges to the steady state relatively quickly.

Figure 9-5. Dynamics of Vehicle Inventory and Average Age under Alternative Policy Implementation Scenarios



SECTION 10.
CONCLUDING OBSERVATIONS

This study had three major goals. The first was to develop a theoretically sound methodology for characterizing the aggregate U.S. LDV inventory and the pathways through which regulatory policy or other scenarios could affect the distribution of the entire vehicle inventory. The second was to conduct a detailed literature review to identify studies providing estimates of the values of several elasticities important for modeling U.S. vehicle markets and vehicle inventory in a manner consistent with the theoretical model and to synthesize available estimates. The third was to develop and parameterize an aggregate simulation model consistent with the theoretical framework and the existing data available from the literature and implement the model to explore the implications of alternative scenarios for U.S. vehicle markets.

Based on our review of the available literature, we found that despite the large number of studies assessing vehicle markets, relatively few quantified our elasticities of interest at an aggregate market level. We found the most robust evidence to be around the aggregate own-price elasticity of demand for new vehicles, with most elasticity estimates falling within a range from −0.37 to −0.90. Estimates accounting for changes in used-vehicle prices were smaller in magnitude, −0.18 and −0.36. Scrappage elasticities had a fairly wide range, but we had less confidence in the values estimated for those that fall at the extremes of our range. Elasticities calculated from studies relying on simulations with varying bounties for scrappage are generally not reported within the studies themselves and are dependent on assumptions and interpretation. We found that the estimated values change considerably with changes in assumptions. If we limit the range to the four studies examining scrappage with respect to used-vehicle prices using other techniques, the range is considerably smaller, from −0.36 to −0.91. Only two studies examined scrappage with respect to new-vehicle prices and those fell in a similar range to the subset of elasticities with respect to used-vehicle prices reflected in the previous sentence (−0.21 and −0.82). Given the lack of studies quantifying aggregate responses in used-vehicle markets or characterizing changes in the total inventory size, determining the extent to which there is consensus was not possible.

In an effort to help fill in the gaps identified from this review, we considered methods to estimate elasticities of used vehicles and inventory size. However, endogeneity caused by the long horizons and equilibrium effects led us to redirect our focus toward development of a broader model framework that would encompass new- and used-vehicle markets within an integrated model with a goal of improving consistency of estimates of the evolution of the U.S. vehicle inventory over time under alternative scenarios. As described in Section 6, we developed an integrated framework that provides insights at an aggregate level and that can be used to conduct rapid scenario analyses. To implement this model, we selected elasticity parameters based on the ranges identified from the literature as our starting points for model parameterization. However, recognizing the considerable uncertainty surrounding these values, particularly in the case of used-vehicle markets and total inventory, we designed the model to be easy to apply with alternative assumptions such that it can be readily used for analyses of alternative transportation policies and scenarios.

10.1 Model Applicability

One of the key insights of this assessment of the literature is that very few existing models in the literature attempted to capture interactions between household demand for new and used vehicles and nonpersonal vehicle transportation. The elasticity values available from the literature are not generally suitable for direct use in policy analysis because they do not capture these interactions. For instance, a study using an estimate of the own-price demand elasticity for new vehicles to estimate the new-vehicle market response to a price shock may substantially overstate the actual change in new-vehicle sales that would result because own-price demand elasticities do not reflect the interactions between new- and used-vehicle markets. Because used-vehicle prices will rise in response to a positive price shock that directly affects the new vehicle market (affecting the degree of substitution between new and used vehicles) and substitution to the outside good is relatively small, the net reduction in new-vehicle sales will be smaller than implied by the own-price elasticity.

Thus, our simulation model aimed to build on the existing literature and fill a gap in the available tools for analyzing aggregate impacts on vehicle markets. Our simulation model can be used to generate policy elasticities that reflect the interactions between these key markets and to estimate net impacts of many different scenarios affecting vehicle markets. It can also be applied directly to simulate aggregate outcomes under specific scenarios, such as regulatory policies that increase the purchase price of new vehicles (and may also simultaneously result in changes in fuel economy or other vehicle characteristics). Because it includes rational expectations, the model can be used to explore market reactions in anticipation of policy implementation as well as the impacts of phasing in policy changes over time. In addition, the model was designed to facilitate sensitivity analyses and can readily be applied to explore the range of outcomes generated using a range of inputs.

10.2 Linkages to Other Models

Although our simulation model makes a valuable contribution to enabling assessment of the aggregate impacts of alternative policies and other scenarios within a theoretically consistent framework, there are many applications where policy analysts may wish to explore impacts at a more disaggregated level. This model could potentially be linked to more disaggregated models in a manner ranging from soft linkages passing policy elasticities or other aggregate outcomes to other models to more formal hard linkages with iteration between the models.

10.3 Limitations and Caveats

As with any model, a number of assumptions underlie our model specification. We drew on relevant elasticities available from the literature, but this literature is limited and there is a fair amount of uncertainty regarding individual elasticity values. We explored a number of different combinations of parameters to assess the relative importance of different parameters and generate a plausible range of responses. However, it is possible that consumer responsiveness to vehicle price changes and substitutability between new and used vehicles and an outside good is changing with the increase in ride-sharing, projected electrification of the vehicle sector in coming decades, potential for widespread adoption of autonomous vehicles, and other major developments that may transform the transportation sector. There are additional gaps in knowledge regarding substitutability between used vehicles of different vintages, relative price responsiveness for new versus used vehicles, and other specific parameters.

In addition, our simulation model is specified at an aggregate level, which may be a limitation for certain applications, though it may be feasible to link to other more disaggregated models as noted above. Although this approach provides an advance in simulating aggregate changes in the vehicle inventory, additional work would be needed to address the stated limitations.

10.4 Priorities for Future Research

One of the findings of this report is that there is considerable uncertainty regarding the key elasticity parameters needed to define the relationship between changes in new-vehicle costs and responses in the new- and used-vehicle markets. Subsequent research that focuses on specification of the relevant elasticities and provides updated estimates of key parameters would be valuable for future scenario analyses. In particular, uncertainty in the aggregate demand elasticity for new vehicles and in the degree of substitution to the outside good appears particularly influential in the overall policy elasticities in Table 7-2. Scrappage elasticities are also important, but less so: the wide range of −0.2 to −1.2 explored in Table 7-2 has a more modest impact on policy elasticities. Our results are less sensitive to the structure of substitution among used vehicles (explored in Appendix C), though increased understanding of consumer preferences in this dimension would also be useful in further narrowing the range of results.

In future work, it may also be possible to expand on the current version of the model to differentiate between market segments; disaggregate alternative-fuel vehicles, especially battery electric vehicles given their expected growth in market share, and otherwise expand on the level of disaggregation incorporated within the model.

Distinguishing between U.S. vehicles being exported from the United States or fully decommissioned when they are scrapped and removed from the U.S. inventory was not a priority for this study, which focused on the U.S. market and vehicle inventory. However, this distinction is potentially an important component of calculating the net global emissions impacts of U.S. policy. Future work could incorporate trade and more fully characterize scrappage to better inform calculations of changes in emissions.

The current model also abstracts from transactions costs, though they may be substantial and could have important effects in the short run. We believe they are much less important for the long-run policy elasticities described in Section 7: as long as the overall lifetime of vehicles does not change too dramatically, the typical number of owners over a vehicle lifespan (and so frequency of transactions) is also unlikely to change by very much. In the short run, high transactions costs could slow down the transition toward the new equilibrium, but we think the effect is small. In the cases we studied, the desired transition is toward slightly older vehicles—perhaps a few months older for a large generalized cost increase. Because this age change is relatively small from the perspective of one individual, it is likely that a person who finds themselves with the "wrong" vehicle after the policy change would simply wait (i.e., letting their current vehicle age a few months) rather than making an extra transaction. The time scales are such that this transaction delay would likely be small relative to the time it will take the overall system to adjust, which is more on the order of decades.

Another limitation is that we abstract from the choice of annual vehicle miles traveled, holding the number of miles driven by any particular vehicle vintage fixed. Further exploration of the decision regarding how much to drive each household vehicle in a year in addition to the decision regarding vehicle ownership may be valuable, though complex. It would additionally rely on estimates of elasticities of demand across vehicles with different odometer readings, separate from age. Here we combine these, effectively looking at demand conditional on a typical odometer reading for a given age.

Although this model could be expanded in a number of ways, it is also important to balance expansion against the ability to conduct rapid analyses. It may be useful to maintain a streamlined aggregate version of the model, in addition to a version that incorporates additional disaggregation and features.

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APPENDIX A:
BIBLIOGRAPHY OF PAPERS INCLUDED IN OUR MAIN SAMPLE

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APPENDIX B:
DETAILED SPECIFICATION OF SCRAP FUNCTION

Following Jacobsen and van Benthem (2015), the scrap rate for vehicles of a given age is given by $s_a = b_a \cdot (p_a)^\gamma$. More elastic scrappage implies that repair cost shocks are relatively dense around the vehicle value: small increases in value therefore make a relatively large number of repairs become worthwhile, reducing scrappage more sharply.

To formalize this define the realization of any given repair cost shock as H_a. The cumulative density function of H_a follows directly from the scrappage function:

$$P\left(H_a \leq \tilde{h}_a\right) = 1 - b_a\left(\tilde{h}_a\right)^\gamma$$

The associated probability density function is:

$$P\left(H_a = \tilde{h}_a\right) = -b_a \gamma \tilde{h}_a^{\gamma-1}$$

defined over the support $\tilde{h}_a \geq \left(\frac{1}{b_a}\right)^{1/\gamma}$. We can then integrate to evaluate the expected repair cost (conditional on the vehicle being repaired, i.e., conditional on $\tilde{h}_a < p_a$) as:

$$h_a \equiv E\left(H_a \middle| \tilde{h}_a < p_a\right) = \frac{b_a^{-1/\gamma}\gamma - b_a \gamma p_a^{1+\gamma}}{(1+\gamma)\left(1 - b_a p_a^\gamma\right)}$$

APPENDIX C:
ADDITIONAL SENSITIVITY ANALYSES, LONG RUN

This appendix contains additional model runs to highlight other scenarios and relationships and perform sensitivity analyses.

Figure C-1 replicates Figure 7-1 for alternative elasticity scenarios. The general patterns are the same, with the higher demand elasticities in Scenario E shifting the curves downward, implying greater policy effects throughout the stock.

Figure C-1. Policy Effect on LDV Stocks as a Function of the Scrappage Elasticity for a 1% Increase in Generalized Cost of New Vehicles

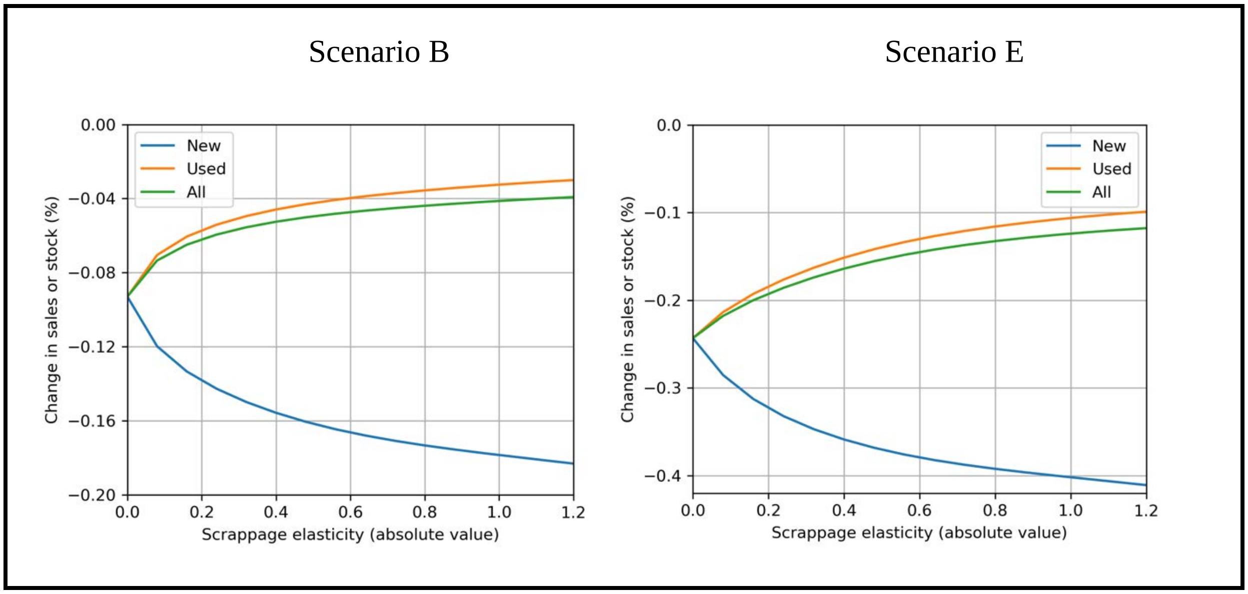


Table C-1 explores sensitivity of the policy elasticities to a range of other assumptions and input parameters. Row (1) reproduces Scenario D from Table 7-2, and the remaining rows explore changes relative to this scenario.

Table C-2. Policy Effect on LDV Stocks, Sensitivity to Additional Parameters

Scenario	Vehicle Demand Elasticities: New-Vehicle Demand	Vehicle Demand Elasticities: Cross-Price New/Used	Vehicle Demand Elasticities: Outside Option	Scrappage Elasticity	Effect of 1% Increase in Generalized Cost of New Vehicles — Quantities (% changes): New	Used	All	Average Age
(1) Scenario D	−0.80	0.05	−0.05	−0.70	−0.25	−0.04	−0.05	0.15
(2) New-outside substitution	−0.80	0.04	−0.05	−0.70	−0.26	−0.04	−0.05	0.16
(3) Double used-vehicle elasticity	−0.80	0.05	−0.05	−0.70	−0.26	−0.03	−0.05	0.18
(4) Half used-vehicle elasticity	−0.80	0.05	−0.05	−0.70	−0.25	−0.05	−0.06	0.14
(5) Zero decline over age difference	−0.80	0.05	−0.05	−0.70	−0.32	−0.04	−0.06	0.23
(6) Double decline with age difference	−0.80	0.05	−0.05	−0.70	−0.20	−0.04	−0.05	0.10
(7) Four times decline with age difference	−0.80	0.05	−0.05	−0.70	−0.14	−0.03	−0.04	0.05
(8) Faster decline for newer vehicles	−0.80	0.05	−0.05	−0.70	−0.27	−0.05	−0.06	0.17
(9) 10% discount rate	−0.80	0.05	−0.05	−0.70	−0.27	−0.04	−0.06	0.17
(10) Baseline survival based on Jacobsen and van Benthem (2015)	−0.80	0.05	−0.05	−0.70	−0.29	−0.04	−0.06	0.17
(11) Baseline survival based on Leard et al. (2017)	−0.80	0.05	−0.05	−0.70	−0.26	−0.04	−0.05	0.15
(12) Baseline depreciation based on caredge.com	−0.80	0.05	−0.05	−0.70	−0.23	−0.03	−0.04	0.14
(13) Small new-vehicle demand elasticity	−0.10	0.01	−0.00	−0.70	−0.06	0.00	0.00	0.02

Row (2) allows part of the substitution away from new vehicles to go to the outside good. In the main text, all of the new-vehicle demand elasticity of −0.8 went to used vehicles; here 25% of it goes to the outside good. The key policy elasticities are not much affected by the source of substitution to the outside good (which is fixed at 0.05).

Row (3) explores an elasticity for older vehicles that rises to double that of new vehicles (i.e. −1.6 rather than −0.8) by age 30. Because new vehicles may be owned by wealthier consumers, who are often shown to be less price sensitive, this case represents a plausible possibility. Policy elasticities are not much affected, though we note that average age increases somewhat more when substitutability among used vehicles is increased. Row (4) explores the opposite case: perhaps older vehicles are more likely to be necessities or the only vehicle a household owns, making their price elasticities smaller. Here, elasticities fall to half (i.e., −0.4 rather than −0.8) for the oldest vehicles. Policy elasticities are not much affected in this scenario.

Rows (5) through (8) explore the way that substitutability relates to the age difference. In Scenario D, the substitution elasticity is set to fall 8% per year of age difference, resulting in a demand system where 49% of substitution away from new vehicles stays within 5 years of age.[42] Very little evidence exists in the literature on substitution across ages, so we explore a wide range of alternative assumptions here. In row (5), all ages are set to be equally good substitutes for new vehicles: the same substitution fraction falls to 32%. This case may still be somewhat realistic because would-be new-vehicle buyers often consider holding on to their, potentially very old, used vehicle instead of buying new. Some degree of substitution across wide age ranges is therefore possible, though we might argue this case is less likely than our main assumption in row (1). In row (6), the rate of drop-off with each year of age difference is doubled. Now, 65% of substitution away from new vehicles stays within 5 years of age. Row (7) quadruples the rate of drop-off such that very high fractions of substitution stay close by in age. Finally, row (8) makes the drop-off fast for newer vehicles (where we think buyers may be sensitive to slight differences across model years) and slow for older vehicles (where we think a few years' age difference may not matter much from the buyer's perspective). In this case, the drop-off rate ranges from 16% (newer vehicles) to 4% (older vehicles) per year of age difference.

[42] Specifically, the demand elasticity matrix is constructed starting with the diagonal—own-price elasticities for different ages—as specified in the input, −0.8 in Scenario D. Cross-price elasticities to other ages are given by the formula $\zeta \cdot (1 - falloff)^{age\_difference}$ where *falloff* is the amount by which the elasticity falls off for each year of age difference, 8% in Scenario D, and ζ is a scalar chosen so that the aggregate cross-price elasticity between new and used vehicles matches the input, 0.05 in Scenario D.

We find that the model results are not overly sensitive to even this very wide range of possibilities for the role of age differences. In row (5), buyers are willing to switch easily to very old vehicles (which have the most potential for long-run reductions in scrappage). This increases the magnitude of the overall policy elasticity for new vehicles somewhat from −0.25 to −0.31. We note that this is a bounding case (in row [5], consumers do not favor low age differences at all), so it represents the maximum policy elasticity along this dimension.

Conversely, in rows (6) and (7) when new-vehicle buyers are unwilling to consider vehicles with big age differences, the policy elasticity falls because the potential for long-run changes in scrappage among relatively new vehicles is small. Because the vehicles that can be saved from scrappage are not great substitutes for new vehicles, new vehicle sales do not fall by as much in equilibrium. The policy elasticity in the quadrupled case in row (7) falls to as low as −0.14 because of this effect. Finally, row (8), with variable degrees of substitutability, is quite close to the original case in row (1).

Row (9) explores a discount rate of 10% instead of 3%. The demand system is recalibrated so that it continues to reproduce baseline vehicle choices even though depreciation is now felt more strongly (because more of residual values are discounted away). Effects on the policy elasticities are small; relative, not absolute, differences in levels of depreciation drive the substitution patterns.

Rows (10) through (12) explore alternative data sources for baseline survival probabilities and rates of depreciation. Effects on the policy elasticities are small.

Finally, row (13) explores a very small demand elasticity for new vehicles. Interestingly, even with this elasticity set very close to zero, the policy elasticity is still much smaller than the demand elasticity at −0.06 versus −0.10. The main effects on quantities and scrappage appear to scale mostly proportionately as the new-vehicle demand effect scales toward zero.

APPENDIX D:
ADDITIONAL SENSITIVITY ANALYSES, TRANSITION PATHS

This appendix contains additional model runs and output to highlight the way myopia influences the dynamic transition and to provide additional cases and sensitivity analysis.

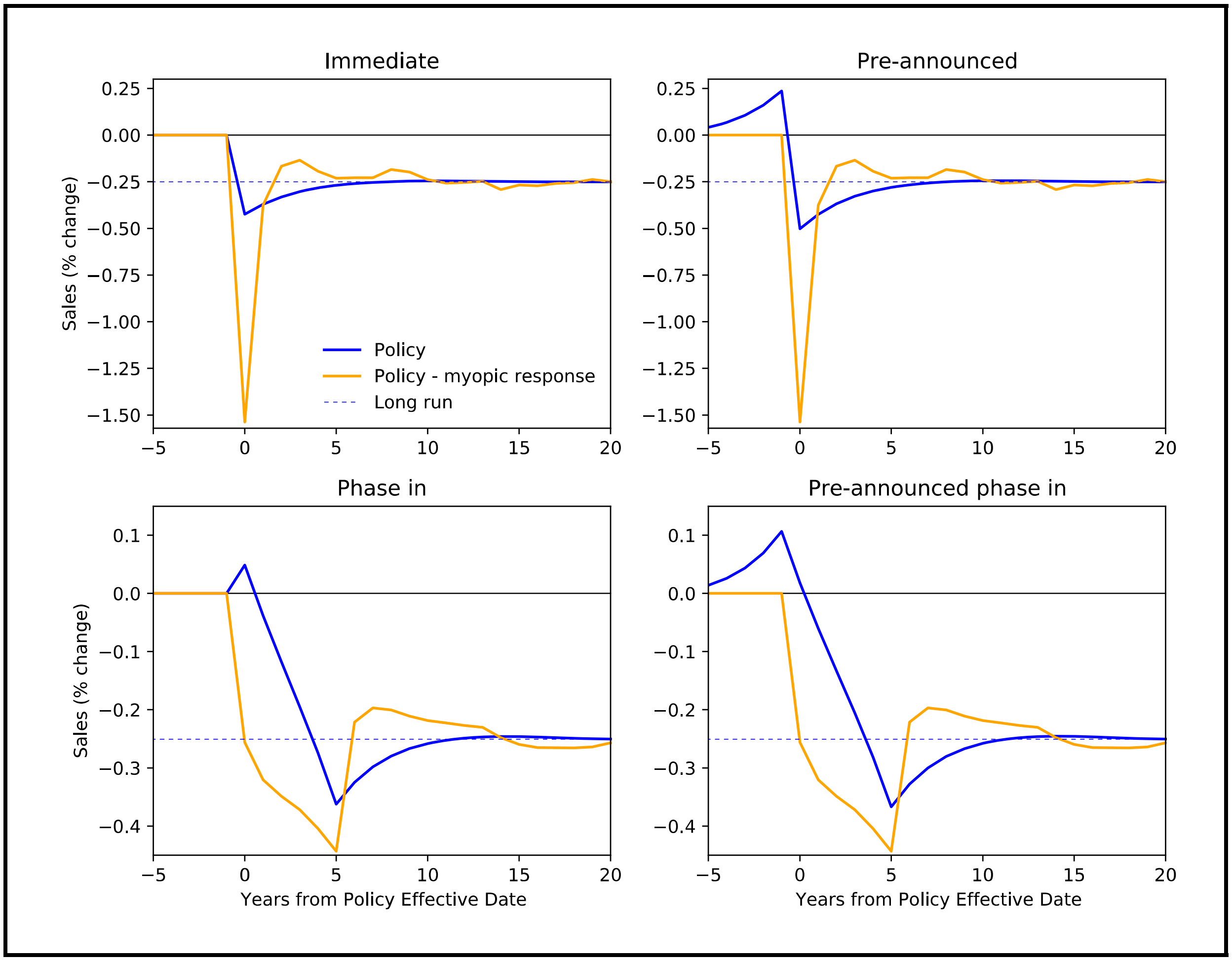
Figure D-1 reproduces Figure 9-1 in the main text, now without allowing consumers to anticipate the changes policy will produce. The blue lines are rational agents, as before, while the orange lines reflect the choices of consumers who believe that the profile of asset values will not change in the future. In the context of new-vehicle purchasers, this would be a consumer who assumes that the trade-in value of a current purchase in 5 years is the present price of 5-year-old vehicles. This results in a large shock to purchases in time period 0: new-vehicle sales fall by 1.5%, exceeding the demand elasticity of 0.8. The reason the decline exceeds the demand elasticity is that new-vehicle buyers believe they will bear a more than 1% ownership cost increase when new-vehicle price rises by 1%. These fully myopic new-vehicle buyers do not allow for any increase in residual value as a result of policy; they think that the lifetime policy cost will fall entirely on the first owner, as opposed to being shared with future owners of the vehicle. This large shock to sales creates, in subsequent time periods, an even greater shortage of inventory in the used-vehicle market. Used prices then overcorrect, rising well above long-run levels and swinging the pendulum the other way. New-vehicle buyers now believe trade-in values will remain very high. This cycle of over- and undershooting continues, with the oscillation still visible many years after the policy is implemented.

The myopic response in the top-right panel is identical to the top-left panel: myopic agents are unaffected by a policy announcement because they only respond to changes in current-period vehicle values.

The response to a phased-in policy with myopia is somewhat gentler because the overshoot in time period 1 is dampened by the fact that the policy is only partly phased in. The myopic time path in this case exhibits the same overshoot and oscillation, but with a lower frequency oscillation than in the top panels. The phase-in spreads the overresponse from the myopic agent over 5 years as opposed to concentrating it in a single year.

In all four cases, the myopic path converges to the same long-run outcome from Table 7-2: the steady state is not affected by this form of myopia because agents do, eventually, assign correct expectations to asset prices.

Figure D-1. Dynamics of New-Vehicle Sales with Myopic Agents



Note: The figure displays the results of two distinct model runs in each panel: blue displays a model run (as in Section 9 of the report) where expectations about used vehicle price responses to policy are correct. In orange, the model is re-run in a world where consumers only expect the part of the change in prices that they can see through immediate equilibrium impacts.

Figure D-2 compares aggregate patterns in the stock when agents are myopic versus forward looking. The heavy lines reproduce the results shown in Figure 9-4, dividing vehicles into three age groups and showing the path taken as the system transitions to its new steady state. The thin lines in the figure show how the system transitions when agents are myopic. With myopia there is a more substantial decline in newer vehicle quantities early on: this reflects the overshooting that happens with myopia and new-vehicle sales. Shortages created by the decline in sales lead to a more dramatic response in the used stock: used-vehicle prices rise very quickly, scrappage falls, and quantity (in green) rises. The myopic system also produces periodic sharp adjustments as agents correct for mistakes in prior periods. In contrast, the forward-looking agents take a smoother trajectory toward the eventual steady state.

One additional point of interest in Figure D-2 is that myopic agents arrive at the aggregate steady state (shown in the blue dashed lines) somewhat more quickly than forward-looking agents do. This is because forward-looking agents build up the vehicle stock early on in preparation for the more stringent phases of the policy and can slightly prolong their arrival at the long-run change.

Figure D-2. Dynamics in the Overall Vehicle Market with Myopic Agents

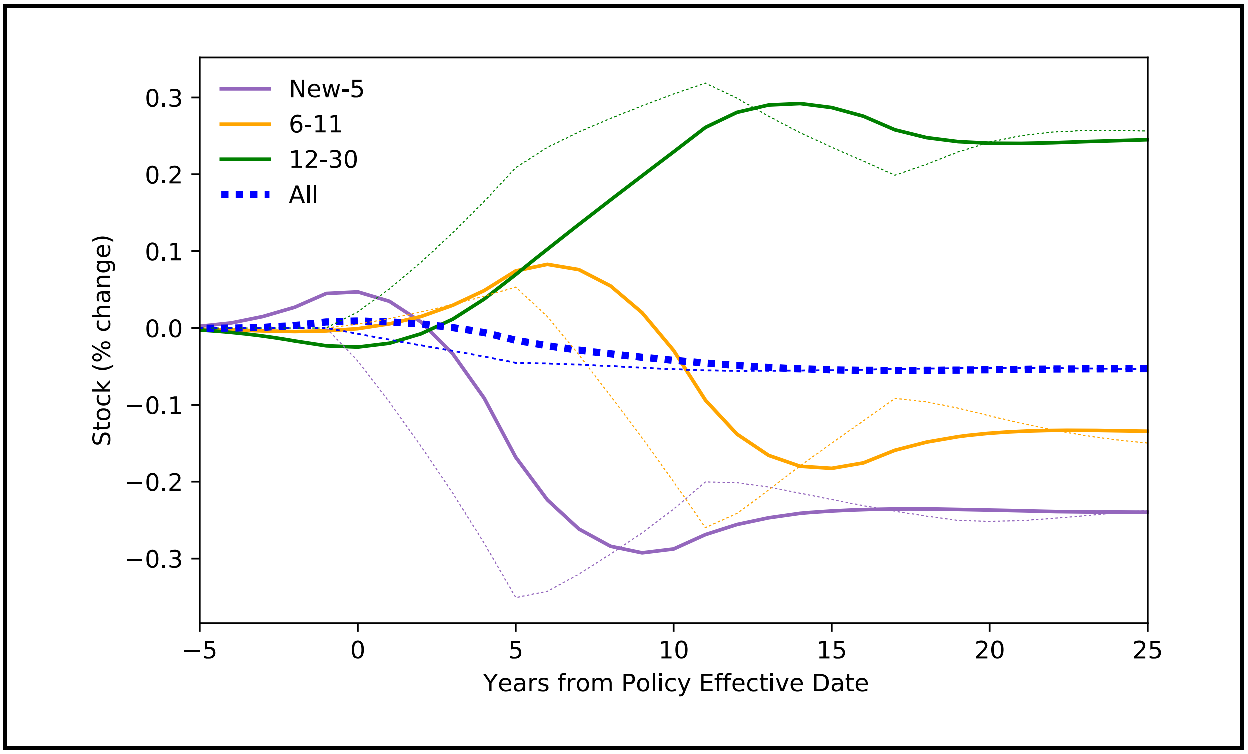


Figure D-3 shows the trajectory of new vehicle sales over time under a range of alternative scenarios. The line for Scenario D reproduces the upper left panel of Figure 9-1, looking at new vehicle sales with immediate policy implementation. The strength of initial impact across scenarios is largely controlled by the demand elasticity (largest for Scenario E). The speed of convergence to the steady-state sales level is similar across scenarios, with somewhat longer time needed to stabilize when the initial impact is larger.

Figure D-3. Dynamics of New-Vehicle Sales with Immediate Policy Implementation Under a Range of Elasticity Scenarios

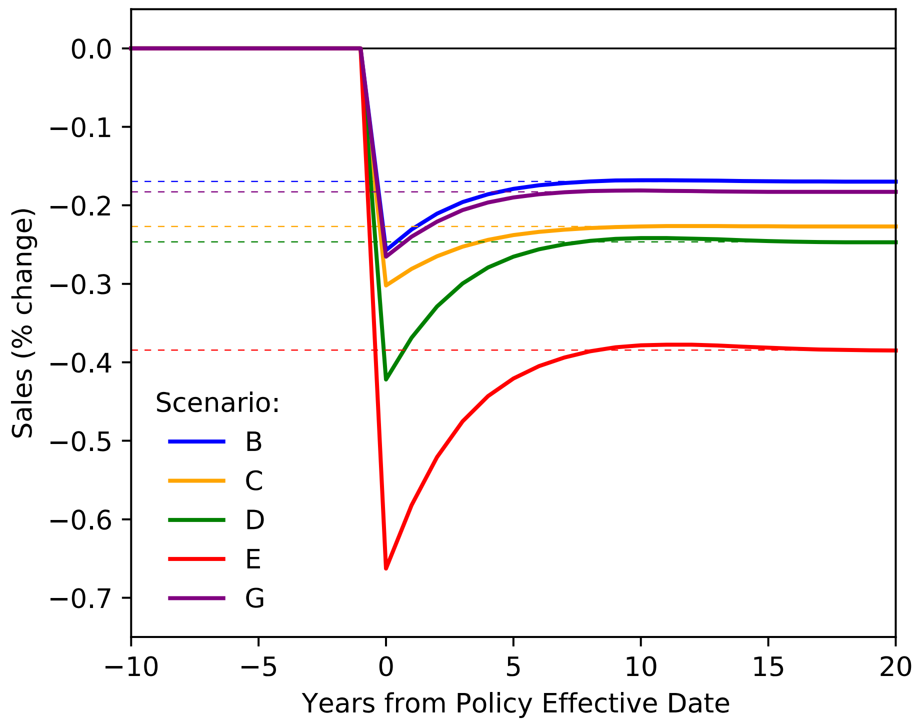
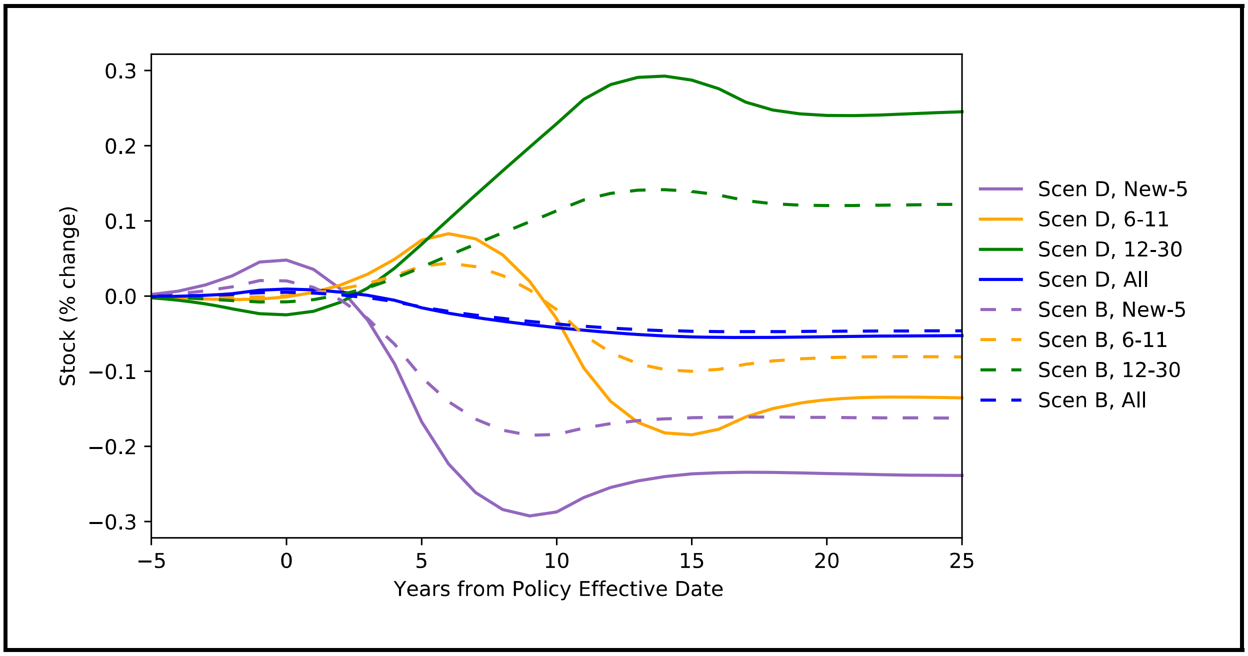


Figure D-4 compares the dynamics of vehicles in different age groups for a preannounced, phased-in policy. The solid lines reproduce the results for Scenario D as presented in Figure 9-4. The dashed lines show results from using the elasticities in Scenario B instead. The long run effects on the entire inventory (in blue) are very similar for scenarios B and D: this reflects the feature that the two scenarios share the same overall elasticity to the outside good (−0.05). The transition paths for individual age categories, however, differ between the two scenarios. In Scenario B, new vehicle demand elasticities are smaller, so less substitution from new to used occurs. New-vehicle inventories (in purple) fall by less and inventories for the oldest vehicles (in green) rise by less in Scenario B.

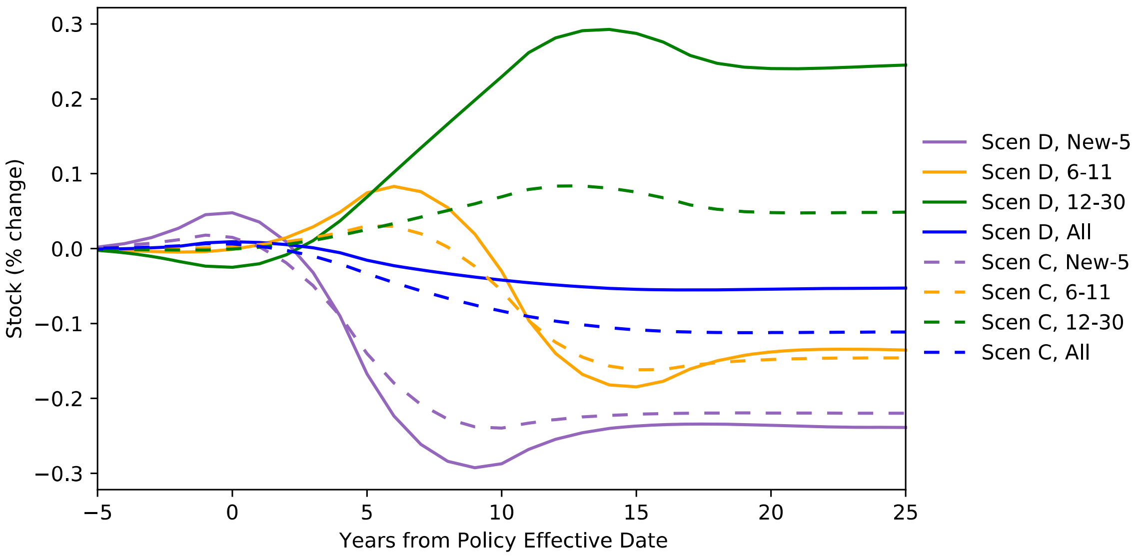
Figure D-4. Dynamics in the Used-Vehicle Market Under Alternative Elasticity Scenarios (Scenarios B and D)



Note: Implementation of the policy is preannounced and phased-in, as in Figure 9-4.

Figure D-5 again reproduces results for Scenario D as shown in Figure 9-4, now comparing Scenario D with Scenario C (dashed lines). Scenario C involves a lower new-vehicle demand elasticity and a higher outside-good elasticity relative to Scenario D. The overall effect on the inventory (shown in blue) is larger in Scenario C because of the more elastic substitution to the outside good. The larger overall effect on the stock in Scenario C competes with the lower new-vehicle demand elasticity in Scenario C to determine the effect on new-vehicle sales (shown in purple). They approximately offset one another, leading to similar long-run effects. The short-run effect on new-vehicle sales is more importantly influenced by the new-vehicle demand elasticity and shows a somewhat larger pre-buying effects, and larger dip afterward, in Scenario D relative to Scenario C.

Figure D-5. Dynamics of the Used-Vehicle Inventory under Alternative Policy Implementation Scenarios: Age 10 Vehicles



Note: Implementation of the policy is preannounced and phased-in, as in Figure 9-4.

APPENDIX E:
APPLICATION OF POLICY ELASTICITIES FOR ANALYSIS OF NEW VEHICLE SALES

This appendix describes the applicability of the policy elasticities of new vehicle sales, for example, as reported in Table 7-2, to settings with large changes in generalized cost or where the short-run path of vehicle sales is of interest.

When the generalized cost of a new vehicle rises, the demand for that vehicle falls, all else equal. This demand change is measured by the demand elasticity. In equilibrium, however, not all else is equal, because a generalized cost increase for new vehicles also increases prices in the used market. New vehicle sales fall less than would be assumed if only looking at the demand elasticity. As explained in the main text, we capture the overall effect on sales in what we term the policy elasticity. It is the percentage change in new vehicle sales, after allowing for changes in the used market, coming from a 1% increase in generalized cost.

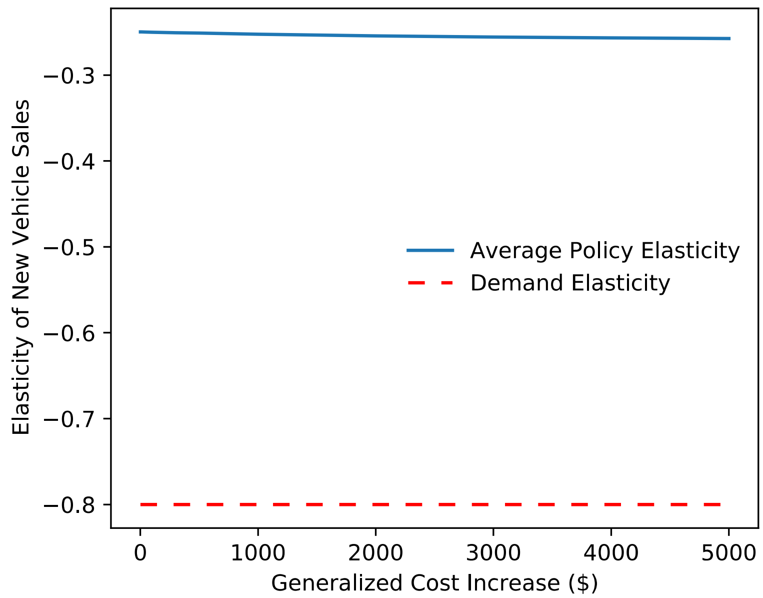
The policy elasticities in the main text are the long-run, steady state change in sales associated with an incremental increase in generalized cost. This document addresses the possibility of applying these long-run, marginal elasticities in two alternative settings: when the generalized cost change is large and in the short run. All values reported below are based on the assumptions of Scenario D in the main text, which assumes a new-vehicle demand elasticity of −0.8 and a scrappage elasticity of −0.7.

E.1 Large Generalized Cost Changes

Figure E-1 shows the average, long-run policy elasticity of new-vehicle sales (vertical axis) for various levels of generalized cost increase (horizontal axis). Note that the vertical axis shows the elasticity (change in sales relative to change in price). The assumed starting new-vehicle cost is $30,000.

The policy elasticity (shown in blue) becomes slightly more negative with large policies but is generally quite stable, going from −0.249 to −0.257 over the range shown. The reason it is so stable likely relates to the underlying constant-elasticity demand and constant-elasticity scrappage equations driving the model. The results in the figure suggest that using a simple policy elasticity calculated at the margin (i.e., based on an incremental change in generalized cost as in the main text) provides a good approximation for the change in sales under a wide range of policies. This is subject to the constant elasticity assumptions that appear elsewhere in the model. The demand elasticity for this model run (−0.8) is shown with the dashed red line for comparison.

Figure E-1. Policy Elasticity of New-Vehicle Sales and the Scale of Generalized Cost



E.2 Short-Run Effect on Sales

Figure E-1 addresses only long-run changes in sales. In the short run, the dynamic effect on sales from a generalized cost increase will generally be different than in the steady state. Figure E-2 displays the policy elasticities produced by the full, dynamic version of the model. Used-vehicle prices do not adjust immediately to their steady state but instead are governed by expectations about asset values and the way the policy works through the fleet (affecting one additional used vintage every year it is in place). We display the dynamic policy elasticity in each year using different assumptions for how the policy is phased in. "Immediate" means that the generalized cost increase is immediate in time 0 and then stays fixed throughout. New-vehicle sales drop more in the short run than in the long run, because in the short run there is a greater "buffer" available in the used fleet. After the policy has been in place for several years, the sales declines in these years mean there are no longer as many used vehicles around to absorb the loss in new-vehicle sales. Prices, and new-vehicle sales, rebound toward the steady state. When the policy is phased in, there are two competing effects in the short run. The buffer of used vehicles is still present as above, tending to produce a sharper drop in sales in the short run. There is now also a competing effect from the announcement of the phase-in. The knowledge that generalized cost will be rising in coming years means that additional sales are encouraged in the early years of the policy, a "pre-buying" effect coming from the increasing stringency in the future. Under a linear phase-in (shown in orange and green), the pre-buying effect outweighs the buffer effect to the point of creating a positive short-run elasticity. With a policy that is phased in but starts more quickly, the two effects could cancel each other more evenly, or the buffer effect could dominate.

In general, it is ambiguous if the short-run policy elasticity will be larger or smaller than the long-run one because of the competing effects. Approximating the policy elasticity in all years with the long-run policy elasticity (in blue dashes) appears to be a reasonable approximation to the dynamics in the first 2 to 3 years and a good approximation once the policy has been in place for 5 years or more. In all cases and all years in the figure, the long-run policy elasticity is a better approximation to the true dynamic effect than the demand elasticity (red dashes).

Figure E-2. Variation in Policy Elasticity of New-Vehicle Sales with Time