Institute for International Economic Policy Working Paper Series
Elliott School of International Affairs
The George Washington University

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IIEP-WP-2016-25

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June 2016

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The Cost of Greening Stimulus: A Dynamic Discrete Choice Analysis of Vehicle Scrappage Programs*

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Abstract

During the recent economic crisis, many countries have adopted stimulus programs designed to achieve two goals: to stimulate economic activity in lagging durable goods sectors and to protect or even enhance environmental quality. The environmental benefits are often viewed and much advocated as co-benefits of economic stimulus. This paper investigates the potential tradeoff between the stimulus and environmental objectives in the context of the popular U.S. Cash-for-Clunkers (CFC) program by developing and estimating a dynamic discrete choice model of vehicle ownership. Results from counterfactual analysis show that design elements to achieve environmental benefits could significantly limit the program impact on demand stimulus: the cost of demand stimulus after netting out environmental benefits under the program could be 43 percent higher in terms of vehicle sales and 38 percent higher in terms of consumer spending than that from alternative policy designs without explicitly aiming at the environmental objective.

Keywords: Stimulus, Dynamic Discrete Choice Model, Vehicle Scrappage

JEL classification: E62, H23, H31, Q85

*We thank participants at the 1st Northeast Workshop on Energy Policy and Environmental Economics, Econometrica Society 2012 summer meeting, Society of Government Economists 2012 conference, and seminars at Bureau of Economic Analysis, Cornell University, Federal Reserve Bank of Atlanta, George Washington University, University of Maryland, and University of Wisconsin - Madison, and the Associate Editor Gautam Gowrisankaran and two anonymous reviewers for helpful comments and suggestions.

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1 Introduction

During the 2008 global economic crisis, many countries implemented the so-called "Green Stimulus" programs. These programs, as defined in Strand and Toman (2010), are "policies and measures to stimulate short-run economic activity while at the same time preserving, protecting and enhancing environmental and nature resource quality both near-term and long-term." Green stimulus programs provide subsidies for a spectrum of activities including improved energy efficiency in buildings and appliances, investment in renewable energy such as solar and wind, investment in new vehicle technology such as battery technology, and accelerated retirement of used vehicles. These programs can be found in stimulus packages across major developed and developing countries. Out of 2.8 trillion dollars in stimulus programs implemented across the globe by July 2009, 15 percent of them are classified as green stimulus (Strand and Toman 2010). In the United States, green stimulus accounted for 12 percent of the nearly 800 billion stimulus package (Barbier 2010).

The environmental benefits from these programs are commonly viewed as co-benefits to economic stimulus, and thus are employed to garner public support for the stimulus programs. The severity of economic downturn and the lack of coordinated international efforts to address climate change make green stimulus programs particularly attractive given their promises of achieving the twin objectives. However, the idea of hitting multiple targets with one policy instrument goes against the principle of efficient policy design. As Tinbergen (1952) pointed out, to achieve multiple policy targets effectively, the number of policy instruments need to be at least as large as the number of targets. This raises the question on the effectiveness of the green stimulus policies, not relative to the baseline of no policy, but relative to alternative designs where the green objective is left to other policy instruments. In other words, are environmental benefits co-benefits to economic stimulus or at the cost of economic stimulus? The goal of this paper is to investigate how the pursuit of the environmental goal impacts the effectiveness of the stimulus objective.

We examine the potential tradeoff between the two objectives in the context of the popular "Cash-for-Clunkers" (henceforth CFC) program in the US, which was set out to stimulate automobile sales and remove fuel inefficient, polluting vehicles from the stock. The program provided eligible consumers \$3500 or \$4500 to purchase a new vehicle and scrap an old vehicle with certain requirements. Alan Blinder in a 2008 article in New York Times argued that Cash-for-Clunkers was "the best stimulus idea you've never heard of" because it can achieve multiple objectives.[1] The program was met with enormous demand: from late July to late Au-

[1] Although Alan Blinder is credited for popularizing the program, his proposal is quite different from how the

gust of 2009, the program provided nearly $3 billions to vehicle buyers engaged in 0.68 million eligible transactions. Such scrappage subsidies have been adopted by China, Japan, and most of the European countries as well. The popularity of this type of stimulus programs makes it an important target for our examination of the potential tradeoff between the twin objectives. Furthermore, programs involving stimulus directed at durable goods are complex because they have long run implications for the characteristics of the stock in use. While the immediate application of our modeling and estimation is to automobiles, the method could be applied to examining efforts to stimulate any durable goods sector hit by a cyclical downturn.

We construct a dynamic stochastic discrete choice model of vehicle ownership featuring vehicle purchase and scrappage decisions at the household level. Faced with aggregate and household-specific economic conditions, each household decides whether to keep a vehicle, whether to sell or scrap the vehicle and purchase a replacement, and if so, what kinds of vehicles to purchase. Our analysis is carried out using national vehicle stock data by vintage-nameplate in 2000, 2005, and 2008 as well as new vehicle sales from 2001 to 2012. Based on model estimates, we conduct counterfactual simulations to examine how the eligibility rules intended for achieving environmental benefits affect the stimulus outcome in terms of vehicle demand and consumer spending. We construct a benchmark CFC policy with age and fuel efficiency requirements on the trade-in and new vehicles following the real program, and compare it with alternative policies with a different mix of environmental goals and consumer-targeting strategies.

Our analysis from a variety of counterfactual scenarios shows that the environmental elements could seriously reduce the amount of demand stimulus either in terms of induced vehicle sales or induced consumer spending. After netting out the environmental benefits, a program without explicitly seeking the environmental objective would be much more cost-effective. The cost of demand stimulus after netting out environmental benefits under the benchmark CFC program could be 43 percent higher in terms of vehicle sales and 38 percent higher in terms of consumer spending than that from alternative policy designs without explicitly aiming at the environmental objective. Furthermore, our simulations show that monetized environmental benefits are only a very small fraction of total scrappage subsidies. Under the benchmark CFC policy, environmental benefits amount to only 0.78 percent of total subsidy payouts, and just two percent of the value of all scrapped trade-in vehicles.

Given the contrast in the magnitude of environmental benefits, a cost-effective program design hinges on how well the program allows better targeting of marginal consumers (those who would not have purchased vehicles without the program) rather than how much the envi-

real program was implemented. His proposal does not contain mpg requirements on new and trade-in vehicles and the requirement of scrappage for trade-in vehicles.

ronmental benefit such a program can achieve. Although in some cases certain environmental elements may allow for better targeting of marginal consumers, thus enhancing both objectives, the additional environmental benefits are small and the cost-effectiveness of such policy can be easily dominated by another program that has no explicit environmental objectives but targets the marginal consumers better. Overall, our findings suggest that the environmental objective could be more effectively addressed by Pigouvian policies targeting vehicle emissions while the demand stimulus operates as a separate targeted program.[2]

While a reduced-form analysis may be sufficient to compare the observed outcomes of the CFCs program against the counterfactual outcome of no policy, a structural approach is needed to construct the outcomes under alternative policy designs with modified eligibility requirements. These alternative policies have not been implemented in reality, and therefore their outcomes cannot be constructed based on a control group without the policy. Moreover, parameters from the reduced-from analysis are usually implicit functions of structural parameters, expectations held by households as well as policy environment. A structural approach has the advantage of conducting policy experiments while keeping the underlying structural parameters unchanged. The dynamic model is motivated by the fact that automobiles are durable goods and a short-term policy such as CFC can have long-term demand and environmental impacts, which are crucial for policy comparisons.

Our work contributes to the literature in the following three dimensions. First, our work adds to emerging empirical studies on vehicle scrappage and subsidy programs in the U.S. and elsewhere during the recent economic downturn (e.g., Copeland and Kahn 2012; Li, Linn and Spiller 2013; Miravete and Moral 2011; Huse and Lucinda 2013; Leheyda and Verboven 2013).[3] All these studies use a static framework to evaluate program impacts on vehicle sales and/or the environmental. To our knowledge, our study is the first to quantitatively evaluate the tradeoff between the stimulus and environmental objectives. Such quantitative evaluations are crucial given that green stimulus programs account for a significant portion of stimulus packages across the globe. Although one should use caution in generalizing our finding to other green stimulus programs, the results serve as an important reminder of the Tinbergen Rule on efficient policy

[2]Automobile usage imposes multiple externalities such as air pollution, congestion and accidents. Appropriate combination of policies are needed to address these externalities. Parry, Walls, and Harrington (2007) offer a detailed discussion on these externalities and Parry and Small (2005) provide an analysis of the gasoline taxes as a (second-best) policy instrument to deal with these externalities.

[3]Copeland and Kahn (2012) investigate the stimulus effect of the U.S. CFC on vehicle sales while Li, Linn and Spiller (2013) examine both the stimulus and environmental impacts of the same program. Miravete and Moral (2011) evaluate the impact of scrappage programs in Spain while Huse and Lucinda (2013) study a recent vehicle subsidy program in Sweden. Leheyda and Verboven (2013) examine the sales and environmental impacts of scrapping subsidies during the recent economic downtown using data from nine countries in Europe.

design, especially in the political climate where policy makers and the public are advocating policies that are set out to achieve multiple goals.

Second, our analysis adds to the literature on the dynamic demand for durable goods such as vehicles, particularly those on the dynamic impact of vehicle scrappage programs. Adda and Cooper (2000, 2007) investigate fiscal impacts of provincial scrappage programs in France and Schiraldi (2011) studies vehicle scrappage subsidy programs in Italy, both in 1990's and without an explicit environmental objective. Gowrisankaran and Rysman (2012) and Schiraldi (2011) show that incorporate dynamics into the demand estimation is feasible and important in understanding the intertemporal substitution and short-run and long-run impacts of policy shocks on the demand for durable goods.

Third, this research is related to Eberly (1994) and Attanasio (2000), both of which use micro data to estimate the parameters of an optimal (S, s) rule for durable good purchases. Their work shares our interest in recovering structural parameters from micro-level household decisions on durable goods. However, the durable purchase decisions in both papers rely on a single attribute, namely the value of durables owned by the households. In our model, vehicle scrappage and purchase decisions depend explicitly upon multiple vehicle attributes. Such an explicit reliance enriches the modeling of vehicle ownership decisions. Our paper is also related to Wei (2013), which studies the endogenous determination of driving, gasoline use and vehicle fuel economy in a dynamic general equilibrium model. However, she assumes exogenous, instead of endogenous scrappage decisions, the latter being the key components of our model.

The paper is organized as follows. Section 2 describes historical data observations. Section 3 details the discrete choice model and aggregate implications. Section 4 describes the empirical strategy. Section 5 presents estimation results and conducts quantitative analysis. Section 6 carries out counterfactual simulations of policy experiments. Section 7 concludes.

2 Program Background and Data

In this section, we first present background information of the CFC program and then describe our data.

2.1 Program Background

Accelerated vehicle scrappage programs provide payment to consumers for scrapping their old and more polluting vehicles. Such programs have been used in many state and local governments in the U.S. and elsewhere in the world as a measure to reduce emissions from automobiles, even before the recession in 2008. The justification for these programs is that old vehicles are more polluting and contribute disproportionately more to air pollution (Kahn 1996). For example, vehicles older than 12 years account for 25 percent of driving in California but 75 percent of total tailpipe emissions in 2010 according to model projections by California Air Resources Board (ARB 2004). Existing literature largely suggest that it is very challenging to design a cost-effective vehicle scrappage program due to the inherent difficulty in screening out the vehicles that are not much used and hence would provide little or no real emissions reduction (Alberini, Harrington and McConnell 1995).

During the recent economic recession, vehicle scrappage programs are given an additional mission of stimulating automobile demand and the economy around the world. In the U.S., the CFC program was established by the Consumer Assistance to Recycle and Save (CARS) Act passed by Congress in June 2009.[4] Officially launched on July 27th, 2009, the program provided eligible consumers a $3,500 or $4,500 rebate when trading in an old vehicle (which would then be dismantled) and purchasing or leasing a new vehicle. Originally, the program was planned as a $1 billion program with an end date of November 1st, 2009. The funding was exhausted within a week and an additional $2 billion was swiftly allocated to program. It was terminated ahead of schedule on August 25th, 2009 when the funding ran out. The program received enormous media attention and many considered the program to be a great success: during the program's nearly one-month run, it generated about 680,000 eligible transactions and had a final cost of $2.85 billion.

The program has multiple eligibility rules for new and trade-in vehicles. There are mpg requirements on both new and trade-in vehicles and the level of subsidy depends on the mpg improvement of the new vehicle over the trade-in vehicle. These rules are imposed to target the environmental objective. In addition, there is maximum age requirement on trade-in vehicles to ensure that the trade-in vehicles would be used without the program and that removing them would generate emissions reduction. The detailed rules are presented in Section 6 before simulations. In the counterfactual simulations, we will examine how these design elements affect program effectiveness on vehicle sales.

The earlier scrappage programs for example in France (1994-1996) studied in Adda and Cooper (2000) and in Italy (1997-1998) studied in Schiraldi (2011) do not have explicit environmental requirements (e.g., mpg or carbon emissions requirements on new or used cars). During

[4] Admittedly, environmental elements of the stimulus program are essential for the bill to secure important votes from democrats. For example, Senator Maria Cantwell, D-Washington, changed her vote to support the plan after President Obama vowed to work with her and others to "maximize the number of efficient cars on America's roads." Senator Dianne Feinstein, D-California advocated for even more stringent eligibility requirements for environmental benefits.

the recent economic downturn, many European countries implemented scrappage programs. Leheyda and Verboven (2013) study the programs in 8 European countries which account for about 90% of the European market: France, Germany, Greece, Italy, the Netherlands, Portugal, Spain and the United Kingdom. The programs in four countries (France, Italy, Portugal, and Spain) have explicit carbon emissions requirement for new vehicles while the programs in other four countries do not have this type of requirement: any new vehicle (or used vehicles less than a certain age) would be eligible.

2.2 Data

The main data source for our estimation is the National Vehicle Population Profile (NVPP) database in year 2000, 2005, and 2008 as well as new vehicle sales from 2001 to 2012. The NVPP is proprietarily maintained by IHS Automotive and contains the number of vehicles registered by nameplate and vintage. In our analysis, we focus on passenger vehicles including passenger cars and light trucks by dropping medium/heavy duty trucks and cargo vans from the data. We match this data set with the fuel economy database by the Environmental Protection Agency (EPA) and vehicle attribute data such as weight and horsepower from Ward's Automotive to generate cross-sectional distributions of vehicles by age, mpg, and other vehicle attributes in 2000, 2005 and 2008.[5]

The matched data set has 26,518 observations and the unit of observation is vintage-nameplate, which is used interchangeably with vehicle model in our discussion. Top three panels of Table 1 provides the summary statistics for each of the three cross-sections of used vehicles. The mean and standard deviation of vehicle attributes are weighted using the number of registrations. The average vehicle age is 8.65 in 2000 and it increased to 9.75 in 2008. This is due to two reasons. First, our data only include vehicles of vintage 1974 and later. As a result, the maximum vehicle age in 2000 data is 27 while it is 35 in 2008 data. Second, vehicles of recent vintages last longer than earlier vintages due to improvement in vehicle technology. The share of passenger cars decreased from 63 percent in 2000 to 55 percent in 2008, partly due to the increasing market share of light trucks in the new vehicle market during the past there decades, and partly due to the longer life span of light trucks than passenger cars.[6] The average mpg stays relatively stable during this period with a slight increase from 2005 to 2008. The last panel presents the

[5]The mpg is the weighted harmonic mean of city mpg and highway mpg based on the formula provided by EPA to measure the fuel economy of the vehicle: mpg = 1/(0.55/city mpg + 0.45/highway mpg).

[6]The market share of light trucks increased from around 20 percent from mid-1970's to 45 percent in 2004. This was largely driven by the introduction of minivan in early 1980's and the increased popularity of SUVs since early 1990's.

summary statistics for new vehicles sold from 2001 to 2012. Compared with vehicle stock, the new vehicles sold have a lower share of cars due to the rapid rise of SUVs from late 1990's into early 2000's. New vehicles are also more fuel-efficient while being heavier and more powerful, a pattern confirmed by the long-term trend in vehicle fleet characteristics in Figure 1.

The top panel of Figure 1 plots the total number of vehicles by vintage at the national level in 2000, 2005, and 2008. Up to year 2000, the number of vehicles within the same vintage is largest in 2000 and smallest in 2008, reflecting scrappage during the period. The upward slope of the three curves is mainly due to scrappage as vehicles age. The fluctuations around the increasing trend reflect sales variations occurred in the new vehicle market in the corresponding year. For example, the large drop in the number of 1996 vintage vehicles observed in all three lines is due to the decrease in new vehicles sales in 1996: the total new vehicle sales was 13.1 million units in 1996, compared to 15.1 and 14.5 million units in 1995 and 1997, respectively.

The bottom panel of Figure 1 shows the average mpg of vehicles by vintage in 2000, 2005, and 2008. The general pattern of the three lines mirrors well the fuel economy of new vehicles in the corresponding year. The rapid rise in mpg from late 1970's to early 1980's was due to high gasoline prices and the Corporate Average fuel economy (CAFE) Standards established in 1978. The increase in mpg after 2003 was largely driven by high gasoline prices and the tightening of CAFE standards for light trucks (from 20.7 in 2004 to 22.5 in 2008). It is interesting to note the difference in average mpg for vehicles of the same vintage across the three years. The difference is more pronounced for vehicles older than 1990 and the average mpg is largest in 2005 and smallest in 2009. This is due to the fact that vehicles of low mpg (such as large or luxury cars or light trucks) tend to survive longer as we will show below.

Figure 2 plots the five-year scrappage rate by vehicle age from 2001 to 2005 in the top graph and the 3-year scrappage rate from 2006 to 2008 in the bottom graph for passenger cars and light trucks separately.[7] For each vehicle type, the scrappage rates are shown for vehicles below median fuel economy and for those above. Three facts emerge from this figure. First, the vehicle scrappage rate tends to increase faster before age 15 and flattens out after that. Second, passenger cars tend to have lower scrappage rate than light trucks among newer vehicles and the opposite is true for older vehicles. Third, within each vehicle type, low mpg vehicles have lower scrappage rate. This could be attributed to the fact that low mpg vehicles tend to be larger, of higher quality, and more expensive. The partial correlation between mpg and scrappage rate, shown to be of opposite sign, can only be analyzed in a regression framework where other vehicle attributes (such as vehicle size and quality) can be controlled for. For example, Li, Timmins,

[7]The five-year scrappage rate for a given vehicle model from 2001 to 2005 is defined as the difference in the number of registrations in 2000 and 2005 divided by the number of registrations in 2000.

and von Haefen (2009) show that the scrappage rate for vehicles over 10 years old decreases as their mpg increases, all else equal and that the relation is stronger when gasoline prices are high. Jacobsen and van Benthem (2011) show that among vehicles older than nine years old, an increase in the gasoline price leads to a higher scrappage rate among fuel efficient vehicles relative to less efficient vehicles.

In addition to the main data on vehicle registration, we collect variables that affect vehicle ownership decisions: the household income distribution from 20000 Census and average annual household income from American Community Survey from 2010 to 2012, annual gasoline prices from the Department of Energy, and average vehicle prices from WARDS Automotive Yearbook, all from 1967 to 2012. The top graph in Figure 3 plots these three variables in 2008 dollars from 1975 to 2012. They are aggregate state variables that affect household decisions in our dynamic model. While household income and vehicle prices have an upward trend, gasoline prices exhibit wide swings during the period.

The bottom graph in Figure 3 depicts annual sales of new vehicle sales, average mpg, weight, and horsepower, both collected from the US EPA Light-Duty Vehicle fuel economy Technology Annual Report 2014. New vehicle sales are pro-cyclical: the correlation coefficient between household income and new vehicle sales is 0.538 from 1975 to 2012. The changes in new vehicle mpg correspond well to movements in gasoline prices in the top graph and they also reflect the changes in CAFE standards over the period. The average mpg reached its peak in 1987 after the Corporate Average Fuel Economy (CAFE) standard was increased to 27.5 for passenger cars in 1985, which has been kept constant ever since. The slight decrease in average mpg from the peak level was largely due to the increasing market share of light trucks which have lower average mpg and lower CAFE standards. The declining average mpg coincided with low and stable gasoline prices from mid-1980s to 2003. After 2003, as gasoline prices took an upward swing, the average mpg of light-duty vehicles increased as well. Weight vehicle and horsepower continue to increase from early 1980's reflecting that automakers are applying new technologies mainly to those dimensions rather than directly to improve mpg (Klier and Linn 2016).

3 The Model

In this section, we construct a dynamic stochastic discrete choice model to characterize household purchase and scrappage decisions under various economic conditions. Our model is closely related to Gowrisankaran and Rysman (2012) and Schiraldi (2011) in that in order to reduce the dimensionality of the state space, we use a pair of scalar-valued sufficient statistics, one for the net utility flow from a particular vehicle, and one for the logit-inclusive value, to characterize the information set of households.

Our model differs from theirs in two important dimensions. First, in order to examine how the CFC program affect household decisions, we explicitly model the tradeoff of desirable vehicle characteristics against its operation costs. While Gowrisankaran and Rysman (2012) and Schiraldi (2011) consider the household's sensitivity to prices or rental prices of the durable goods, we explicitly consider their sensitivity to fuel costs, an important consideration for the CFC program participants. Second, given the economic background of the CFC program and our consideration of fuel costs, macroeconomic variables, in particular aggregate income and gasoline prices, may affect evolutions of both the net utility flow from a particular vehicle, but also the logit-inclusive value that summarizes the evolving outside option of purchasing other vehicles. In our model, we explicitly take into account the impact of current income and gasoline prices on both the future utility stream of owning a particular vehicle and the evolving outside option.

We maintain a simplifying assumption common to Adda and Cooper (2000) and Schiraldi (2011) for computational tractability. A household can at most own one vehicle at each period. This amounts to assuming that in multi-vehicle households, decisions over each of the vehicles are separate.

3.1 Household's Optimization Problem

3.1.1 State Variables

We classify households as vehicle owners or non-owners based upon whether they enter a particular period with a vehicle or not. Let $\mathbf{j}_t$ denote the set of new vehicles available in period t, and $\mathcal{J}_t = \{j,\, j \in \left\{\cup_{\varkappa=1}^{t} \mathbf{j}_\varkappa\right\}\}$ denote the set of all vehicle models available in the primary or secondary market. In each period a household can start the period with a vehicle $j \in \mathcal{J}_t$, or without any vehicles, which we denote as $j = 0$. Each household faces a set of state variables that can be categorized into aggregate and household-specific state variables. The aggregate state of the economy at time t is characterized by two state variables: the average household income Y_t and the real gasoline price O_t. We use $\mathbf{S}_t \equiv \{Y_t, O_t\}$ to denote the vector of aggregate state variables. We assume that $\mathbf{S}_t$ follows a joint first-order Markov process. We denote the set of state variables specific to household i as Ω_{it}, which includes current product attributes and prices, the number of models $\mathcal{J}_t$, and any other market characteristics that may affect the firms' product pricing, entry, exit or changes in future model attributes. In general, it includes all variables in household i's information set at period t that affect its maximization decisions, in addition to those contained in $\mathbf{S}_t$. We assume that Ω_{it} evolves according to a stochastic process $\Pi\left(\Omega_{it+1}|\Omega_{it}, \mathbf{S}_t\right)$ that will account for firm optimizing behavior.

Each household also privately observes a vector of choice-specific idiosyncratic taste shocks $\epsilon_{\mathbf{it}} = (\epsilon_{i0t}, \epsilon_{i1t}, ...\epsilon_{iJ_tt})$, where ϵ_{i0t} corresponds to the option of not owning any vehicles, and ϵ_{ijt} corresponds to the jth option from $\mathcal{J}_t$. These shocks, unobservable to researchers, follow an identical and independent type-I extreme value distribution across households, periods and vehicle models.

We assume that household income, Y_{it}, has two components: the national average household income Y_t and the individual household's idiosyncratic deviation from the average. We model the process of the household average income while treating the household deviation as a permanent draw from a given distribution. Specifically, we draw household income from 2000 Census and construct the income deviation from the national average. We assume that households are heterogeneous in their preferences for vehicle characteristics. Household types are defined by their permanent differences in idiosyncratic income and heterogeneous preferences.

3.1.2 Choice Set of Households

Time is infinite and discrete. Given a set of state variables, households maximize their lifetime utility by making vehicle ownership decisions. The decisions are made at the beginning of each period. A vehicle owner can choose to: (1) keep the vehicle, (2) sell or scrap the vehicle and buy a new or used vehicle from the set $\mathcal{J}_t$; or (3) sell or scrap the vehicle and become a non-owner. A non-owner can choose to: (1) remain a non-owner, or (2) buy a new or used vehicle from the set $\mathcal{J}_t$. We describe household decisions using vector $\psi = \{d, j\} \in \Psi$. Here d takes on two values. When $d = 1$, either the vehicle-owner or non-owner decides to keep the status quo. When $d = 0$, the vehicle owner decides not to keep the current vehicle, while the non-owner decides to purchase a vehicle. When $d = 0$, the variable $j \in \mathcal{J}_t \cup \{0\}$ denotes the optimal choice from the set of the new vehicle model plus the choice of not owning any vehicles. We assume that households can enjoy services of vehicles the same period when purchase decisions are made.

3.1.3 Contemporaneous Utility Function

The contemporaneous utility function of households depends upon the aggregate state variables, the household's status of vehicle ownership at the beginning of the period, corresponding household-specific state variables, and the decisions ψ_t made by the households.

Each vehicle model $j \in \mathcal{J}_t$ is characterized by observed physical characteristics x_{jt} (vehicle type, i.e., car or truck, g_k; vehicle age, a_k; horsepower, h_k; weight, w_k; fuel efficiency, e_k;), price p_{jt}, and the unobserved product characteristics ξ_{jt}. A household derives the following contemporary utilities for each of its possible choices at time t. If the household which owns a vehicle $k \in \mathcal{J}_t$ plans to keep it, it gets utility

$$\widetilde{u}_{it}^{kk} = F_i^k\left(k, \Omega_{it}, \mathbf{S}_t\right) + \epsilon_{ikt}, \tag{1}$$

where $F_i^k\left(k, \Omega_{it}, \mathbf{S}_t\right)$ is a function of vehicle attributes (x_{jt}, p_{jt}, and ξ_{jt}), the household-specific information set Ω_{it}, and the aggregate state variables $\mathbf{S}_t$. Among the attributes, the age and price of vehicle k change over time to reflect the deterioration of vehicle conditions over tiime.

For a vehicle-owner, the contemporary utility from keeping the vehicle has two components. On the one hand, the household takes utility from services of vehicle k, which depend upon attributes such as age, horsepower and weight. On the other hand, the household also needs to pay for fuel costs. We assume that fuel costs for vehicle k in period t can be represented as $f\left(a_{k,}g_k, e_k, O_t\right)$, a function of gasoline prices, and the age, type and fuel efficiency of vehicle k. We model fuel costs incurred as utility loss for the household. The sensitivity of households to fuel costs and vehicle prices is modelled as inversely proportional to income.

Specifically, $F_i^k\left(k, \Omega_{it}, \mathbf{S}_t\right)$ takes the following functional form:

$$\begin{aligned} F_i^k\left(k, \Omega_{it}, \mathbf{S}_t\right) &= \varphi_{i,0,g_k} + \varphi_{1,g_k}\log\left(a_{kt}\right) + \varphi_{2,g_k}\left[\log\left(a_{kt}\right)\right]^2 \\ &\quad + \varphi_{h,g_k}\log\left(h_k\right) + \varphi_{i,w,g_k}\log\left(w_k\right) + \varphi_\xi \xi_{kt} \\ &\quad - \frac{\alpha}{Y_{it}} f\left(a_{k,}g_k, e_k, O_t\right), \end{aligned} \tag{2}$$

where we assume that parameters differ based on whether vehicle k is a car or truck. The parameter, $\varphi_{i,0,g_k}$, represents household i's utility from auto service per se, conditional on vehicle type (car or truck), but regardless of other attributes. The parameters ϕ_{1,g_k} and ϕ_{2,g_k} govern the non-linear dependence of utility upon the vehicle age. Parameters $\varphi_{h,g_k}, \varphi_{i,w,g_k}, \varphi_\xi$ and α capture respectively the dependence of utility upon horsepower, weight, the unobserved component of vehicle, and fuel costs. The dependence of utility on vehicle attributes differs across vehicle types. We incorporate household heterogeneity in terms of the constant term, $\varphi_{i,0,g_k}$, the coefficient for vehicle weight, φ_{i,w,g_k}, and household income Y_{it}. In the empirical analysis, $\varphi_{i,0,g_k}$ and φ_{i,w,g_k} are assumed to have normal distribution and their means and standard deviations will be estimated.

If the household sells the currently owned vehicle and purchase a different vehicle $j \in \mathcal{J}_t$, the household pays the price p_{jt}, and the transaction costs τ for the new vehicle, and receives the value of its sold vehicle, p_{kt}. We assume that transaction costs, τ, in the form of utility loss, are sustained by the household each time a used or new vehicle is purchased. The transaction costs capture the presence of search costs, financial costs, switching costs, asymmetric information and so on. The household gets utility:

$$\widetilde{u}_{it}^{kj} = F_i^j \left(j, \Omega_{it}, \mathbf{S}_t \right) \cdot \mathbf{I} \left(j \neq 0 \right) - \frac{\alpha}{Y_{it}} \left(p_{jt} - p_{kt} \right) - \tau \cdot \mathbf{I} \left(j \neq 0 \right) + \epsilon_{ijt}. \tag{3}$$

If the household sells its current vehicle, but opts for the outside option of no vehicles, it gets utility

$$\widetilde{u}_{it}^{k0} = \frac{\alpha}{Y_{it}} p_{kt} + \epsilon_{i0t}, \tag{4}$$

where we assume no transaction costs in choosing the outside option.

A non-vehicle owner at the beginning of period t has two options, purchasing a vehicle or remaining a non-owner. If purchasing a new vehicle, it gets utility $\widetilde{u}_{it}^{0j}$; while if remaining a non-owner, it gets utility $\widetilde{u}_{it}^{00}$, with p_{0t} set to zero.

3.2 Value Functions of Vehicle Owners and Non-owners

Let $\widehat{V}_i \left(k, \mathbf{\Omega}_{it}, \mathbf{S}_t, \epsilon_{it} \right)$ represent the value function of household i given the information set $\{\mathbf{\Omega}_{it}, \mathbf{S}_t\}$ and realizations of preference shocks ϵ_{it}. Given the aggregate and individual state variables, the household decides whether to keep the currently-owned vehicle, scrap or sell the vehicle and replace it with a new one, or just not own any vehicles.

Following the literature, we make the conditional independence assumption: conditional on the decision (ψ) and the state variables in $\{\mathbf{\Omega}_{it}, \mathbf{S}_t\}$ in the current period, the state variables in the next period (Ω_{it+1}) do not depend on current idiosyncratic shocks (ϵ_{it}). The value function of vehicle owners ($k \neq 0$) and non-owners ($k = 0$), $\widehat{V}_i \left(k, \mathbf{\Omega}_{it}, \mathbf{S}_t, \epsilon_{it} \right)$, is given by,

$$\widehat{V}_i \left(k, \mathbf{\Omega}_{it}, \mathbf{S}_t, \epsilon_{it} \right) = \max_{\psi \in \Psi} \left\{ \begin{array}{c} \widetilde{u}_{it}^{kk} + \beta \mathbb{E} \widehat{V}_i \left(k, \mathbf{\Omega}_{it+1}, \mathbf{S}_{t+1}, \epsilon_{it+1} | \mathbf{\Omega}_{it}, \mathbf{S}_t, \epsilon_{it} \right), \\ \max\limits_{j \in \mathcal{J}_t} \left\{ \widetilde{u}_{it}^{kj} + \beta \mathbb{E} \widehat{V}_i \left(j, \mathbf{\Omega}_{it+1}, \mathbf{S}_{t+1}, \epsilon_{it+1} | \mathbf{\Omega}_{it}, \mathbf{S}_t, \epsilon_{it} \right) \right\}, \\ \mathbf{I} \left(k \neq 0 \right) \left[\widetilde{u}_{it}^{k0} + \beta \mathbb{E} \widehat{V}_i \left(0, \mathbf{\Omega}_{it+1}, \mathbf{S}_{t+1}, \epsilon_{it+1} | \mathbf{\Omega}_{it}, \mathbf{S}_t, \epsilon_{it} \right) \right]. \end{array} \right\} \tag{5}$$

The first option is to keep the status quo, either to keep the same vehicle for an owner, or to continue owning no vehicles for a non-owner. The second option is to purchase a new or used vehicle from the available set $\mathcal{J}_t$. The third option is specific for vehicle-owner to sell the currently-owned vehicle and become a non-owner.

The state space involving $\mathbf{\Omega}_{it}$ is too large for the household's dynamic vehicle ownership decisions. We make assumptions to reduce the dimensionality of the state space, and to make the computational problem tractable.

3.2.1 A Sufficient Statistics for Net Utility Flow

We follow Schiraldi (2011) in our first step of simplification by subtracting the price of the currently-owned vehicle from equation (5) and redefining $V_i\left(k, \mathbf{\Omega}_{it}, , \mathbf{S}_t, \epsilon_{it}\right) = \widehat{V}_i\left(k, \mathbf{\Omega}_{it}, , \mathbf{S}_t, \epsilon_{it}\right) - \frac{\alpha}{Y_{it}} p_{kt}$. In the case of $k = 0$, we have $V_i\left(0, \mathbf{\Omega}_{it}, , \mathbf{S}_t, \epsilon_{it}\right) = \widehat{V}_i\left(0, \mathbf{\Omega}_{it}, , \mathbf{S}_t, \epsilon_{it}\right)$.

Substituting equations (1) to (4) into equation (5), we can rewrite the value function as

$$V_i\left(k, \mathbf{\Omega}_{it}, \mathbf{S}_t, \epsilon_{it}\right) = \max_{\psi \in \Psi} \left\{ \begin{array}{c} \mathbf{I}\left(k \neq 0\right) \left\{ F_i^k\left(k, \Omega_{it}, \mathbf{S}_t\right) - \frac{\alpha}{Y_{it}} \left\{ p_{kt} - \beta \mathbb{E}_t \left[\frac{Y_{it}}{Y_{it+1}} p_{kt+1} \right] \right\} \right. \\ \left. + \epsilon_{ikt} + \beta \mathbb{E} V_i\left(k, \mathbf{\Omega}_{it+1}, \mathbf{S}_{t+1}, \epsilon_{it+1} | \mathbf{\Omega}_{it}, \mathbf{S}_t, \epsilon_{it}\right) \right\}, \\ \max\limits_{j \in \mathcal{J}_t} \left\{ F_i^j\left(j, \Omega_{it}, \mathbf{S}_t\right) - \frac{\alpha}{Y_{it}} \left[p_{jt} - \beta \mathbb{E}_t \left(\frac{Y_{it}}{Y_{it+1}} p_{jt+1} \right) \right] - \tau \right. \\ \left. + \epsilon_{ijt} + \beta \mathbb{E} V_i\left(j, \mathbf{\Omega}_{it+1}, \mathbf{S}_{t+1}, \epsilon_{it+1} | \mathbf{\Omega}_{it}, \mathbf{S}_t, \epsilon_{it}\right) \right\}, \\ \epsilon_{i0t} + \beta \mathbb{E} V_i\left(0, \mathbf{\Omega}_{it+1}, \mathbf{S}_{t+1}, \epsilon_{it+1} | \mathbf{\Omega}_{it}, \mathbf{S}_t, \epsilon_{it}\right). \end{array} \right\} \tag{6}$$

The transformation is helpful to define a sufficient statistics to capture the net augmented utility flow each period. Such a sufficient statistics can be used to summarize information on vehicle prices and attributes, and capture the depreciation of the vehicle over time. Specifically we denote the net augmented utility flow from vehicle k in period t as

$$\phi_{ijt} = \mathbf{I}\left(j \in \mathcal{J}_t\right) F_i^j\left(j, \Omega_{it}, \mathbf{S}_t\right) - \frac{\alpha}{Y_{it}} \left[p_{jt} - \beta \mathbb{E}_t \left(\frac{Y_{it}}{Y_{it+1}} p_{jt+1} \right) \right], \tag{7}$$

where $\left[p_{jt} - \beta \mathbb{E}_t \left(\frac{Y_{it}}{Y_{it+1}} p_{jt+1} \right) \right]$ is the adjusted rental price of vehicle j in period t, taking into account that the household's sensitivity to the vehicle price next period depends upon possible changes in household income from period t to $t+1$. Based upon the definition of $F_i^j\left(j, \Omega_{it}, \mathbf{S}_t\right)$, the net utility flow ϕ_{ijt} accounts for utility flow from vehicle attributes, fuel costs, and the (adjusted) rental price. It includes elements of both household and vehicle characteristics.

3.2.2 The Logit-Inclusive Value for Purchase Options

Because ϵ_{it} is not observed by researchers, we can define the integrated (or ex ante) value function for owners and non-owners as the continuation value right before ϵ_{it} is revealed:

$$\overline{V}_i\left(k, \mathbf{\Omega}_{it}, \mathbf{S}_t\right) = \int_{\epsilon_{it}} V_i\left(k, \mathbf{\Omega}_{it}, , \mathbf{S}_t, \epsilon_{it}\right) dG(\epsilon_{it}), \tag{8}$$

where $G(\epsilon_{it})$ represents the cumulative distribution function of ϵ_{it}.

The integrated value functions defined above will be used to form choice probabilities which are then used for empirical analysis. Following Rust (1987), they are the unique solution to the integrated Bellman equations for vehicle owners and non-owners:

$$\overline{V}_i\left(k,\mathbf{\Omega}_{it},\mathbf{S}_t\right)=\int \max_{\psi\in\Psi}\left\{\begin{array}{c}\mathbf{I}\left(k\neq 0\right)\left[\phi_{ikt}+\epsilon_{ikt}+\beta\mathbb{E}\overline{V}_i\left(k,\mathbf{\Omega}_{it+1},\mathbf{S}_{t+1}|\mathbf{\Omega}_{it},\mathbf{S}_t\right)\right]\\ \max\limits_{j\in\mathcal{J}_t}\left\{\phi_{ijt}-\tau+\epsilon_{ijt}+\beta\mathbb{E}\overline{V}_i\left(j,\mathbf{\Omega}_{it+1},,\mathbf{S}_{t+1}|\mathbf{\Omega}_{it},\mathbf{S}_t\right)\right\}\\ \epsilon_{i0t}+\beta\mathbb{E}\overline{V}_0\left(0,\mathbf{\Omega}_{it+1},,\mathbf{S}_{t+1}|\mathbf{\Omega}_{it},\mathbf{S}_t\right)\end{array}\right\}dG(\epsilon_{it}). \tag{9}$$

The value function can be further simplified by using the aggregation properties of the type I extreme-value distribution of ϵ_{ijt}. Based on those properties, the expected value of the best purchase choice from the available set $\mathcal{J}_t$ can be expressed as the logarithm of the sum of the mean expected discounted utility of each option and for each household. Specifically, the maximum expected utility from purchasing new or used vehicles is given by the logit inclusive value, δ_{it} :

$$\delta_{it}=\ln\left(\sum_{j\in\mathcal{J}_t}\exp\left(\phi_{ijt}-\tau+\beta\mathbb{E}\left[\overline{V}_i\left(j,\mathbf{\Omega}_{it+1},\mathbf{S}_{t+1}\right)|\mathbf{\Omega}_{it},\mathbf{S}_t\right]\right)\right). \tag{10}$$

In order to reduce the dimension of state space, we follow Gowrisankaran and Rysman (2012) and Schiraldi (2011) in making two crucial assumptions. First we assume that the vectors $\{\phi_{ikt},\delta_{it},\mathbf{S}_t\}$ contain all the relevant information in $\{\mathbf{\Omega}_{it},\mathbf{S}_t\}$ to obtain the probability distribution of $\{\phi_{ikt+1},\delta_{it+1}\}$ conditional on $\{\mathbf{\Omega}_{it},\mathbf{S}_t\}$. This assumption can be interpreted as bounded-rational households form expectations using only a subset of information available for them. Second, we assume that their expectations of $\{\phi_{ikt+1},\delta_{it+1}\}$ follow specific functional forms. We assume that each household perceives the evolutions of the net augmented utility flow ϕ_{ijt} and the logit-inclusive values δ_{it} as taking the following stochastic processes:

$$\delta_{it+1} = \rho_{1i}+\rho_{2i}\delta_{it}+\rho_{3i}Y_t+\rho_{4i}O_t+\eta_{it+1}, \tag{11}$$

$$\phi_{ijt+1} = \gamma_{1i}+\gamma_{2i}\phi_{ijt}+\gamma_{3i}\delta_{it}+\gamma_{4i}Y_t+\gamma_{5i}O_t+\upsilon_{it+1}. \tag{12}$$

where η_{it} and υ_{it} are independent across time, across each other, and normally distributed. Both constants and coefficients in the stochastic processes are specific to each household. Equation (11) takes into account the predictive component in δ_{it}, which captures prices and characteristics of products available. Different from Gowrisankaran and Rysman (2012) and Schiraldi (2011), who only include the current purchase options δ_{it} in predicting the next period option value, we also include two macro variable, average output Y_t and gasoline prices O_t in the current period, for the household to form expectation for the next period.

The two macro variables are state variables in the underlying discrete choice model. While we reduce dimensionality by assuming that many different quality of market characteristics lead to the same transition probabilities to the next-period state in the current framework, we consider the inclusion of Y_t and O_t in the transition a better approximation in our framework. In particular, a combination of high income and high gasoline prices may generate the same logit-inclusive value δ_{it} in the current period as a combination of low income and low gasoline prices. However, since aggregate income and gasoline prices have their distinctive stochastic processes, it is likely that the two combinations that generate the same logit-inclusive value in the current period may not evolve into another two sets of combinations that correspond to the same δ_{it+1}. In other words, δ_{it} may not be sufficient to capture the information contained in the aggregate income and gasoline prices. By including the two macro variables that are in the information set of the household's decision problem, we take into account the particular transition processes of these two variables and their distinct impact on household purchase decisions.

These two assumptions essentially transform the household's value function into a decision problem with four state variables: $\{\phi_{ikt}, \delta_{it}, Y_t, O_t\}$. Under the previous assumptions, we can write the Bellman equation (9) as,

$$\begin{aligned} \overline{V}_i\left(\phi_{ikt}, \delta_{it}, \mathbf{S}_t\right) \;=\; & \ln\Big\{ \exp\left(\delta_{it}\right) + \exp\left[\beta \mathbb{E} \overline{V}_0\left(0, \delta_{it+1}, , \mathbf{S}_{t+1} | \delta_{it}, \mathbf{S}_t\right)\right] \\ & + \mathbf{I}\left(k \neq 0\right) \exp[\phi_{ikt} + \beta \mathbb{E} \overline{V}_i\left(\phi_{ikt+1}, \delta_{it+1}, \mathbf{S}_{t+1} | \phi_{ikt}, \delta_{it}, \mathbf{S}_t\right)] \Big\}. \end{aligned} \tag{13}$$

The explicit inclusion of output and gasoline prices is consistent with our consideration of fuel costs as part of operation expenses of owning vehicles. We thus build in the impact of aggregate macro variables on households' purchase behavior, which is an important consideration for the cash-for-clunkers program.

3.3 Household Choices

In this section, we describe the household's optimal decisions on whether to scrap or sell a vehicle, whether to purchase another vehicle, and if purchasing a vehicle, which one to choose from available models. We then proceed to examine the impact of aggregate state variables and scrappage subsidies on optimal decision making.

The decision on selling or scrapping the vehicle is essentially an optimal stopping problem.

The household decides whether to sell or scrap the vehicle in the current period, or delay the decision and retain the option value to wait for more favorable aggregate states in the next period.

Given the type-I extreme value distribution of idiosyncratic taste shocks, for the ith household, the aggregate probability of keeping the status quo with $k \in \{\mathcal{J}_{t-1}, 0\}$, given the state $\{\delta_{it}, \mathbf{S}_t\}$ is a logistic function:

$$\mu_i^{kk}(\phi_{ikt}, \delta_{it}, \mathbf{S}_t) = \frac{\exp\left[\phi_{ikt} + \beta \mathbb{E} \overline{V}_i(\phi_{ikt+1}, \delta_{it+1}, \mathbf{S}_{t+1} | \phi_{ikt}, \delta_{it}, \mathbf{S}_t)\right]}{\exp[\overline{V}_i(\phi_{ikt}, \delta_{it}, \mathbf{S}_t)]}, \tag{14}$$

where $\overline{V}_i(\phi_{ikt}, \delta_{it}, \mathbf{S}_t)$ is defined in equation (13). Accordingly, the aggregate probability that household i with good $k \in \mathcal{J}_{t-1} \cup \{0\}$ purchase a good $j \in \mathcal{J}_t \cup \{0\}$ is

$$\mu_i^{kj}(\phi_{ikt}, \delta_{it}, \mathbf{S}_t) = \frac{\exp\left[\phi_{ijt} + \beta \mathbb{E} \overline{V}_i(\phi_{ijt+1}, \delta_{it+1}, \mathbf{S}_{t+1} | \phi_{ikt}, \delta_{it}, \mathbf{S}_t)\right]}{\exp[\overline{V}_i(\phi_{ikt}, \delta_{it}, \mathbf{S}_t)]}. \tag{15}$$

where $\mathbf{I}(k \neq 0)\, \mu_i^{kk} + \sum_{j \in \mathcal{J}_t \cup \{0\}} \mu_i^{kj} = 1$.

The aggregate state variables, $\{Y_t, O_t\}$, play important roles in the household's decisions. Aggregate income and gasoline prices are state variables for their own sake, but they also affect evolutions of the other two state variables $\{\phi_{ikt}, \delta_{it}\}$. Those effects stem from the impact of changes in aggregate income or gasoline prices on household decisions. An increase in current aggregate income, Y_t, reduces the household's price sensitivity to vehicle purchase and operation costs. As a result, an increase in current aggregate income is likely to encourage vehicle purchases.

An increase in gasoline prices, O_t, raises the fuel cost of driving all vehicles. The increase in driving costs affects vehicle ownership decisions. Faced with larger increase in fuel costs, a household owning a fuel-inefficient vehicle needs to weigh the continuing utility from driving such a vehicle against higher fuel costs to decide on whether to sell or scrap the vehicle for a different model. Higher gasoline prices may provide incentives to sell or scrap those aged and fuel-inefficient vehicles and purchase more fuel efficient new vehicles. On the other hand, higher gasoline prices increase vehicle operation costs and monetary burden, and consequently may delay households' purchase decisions.

3.4 Scrappage Subsidies and Aggregate Implications

3.4.1 Impacts of Scrappage Subsidies

In our model, scrappage subsidies may reduce costs of purchasing new vehicles. Based on the optimal decision rules described above, scrappage subsidies affect household decisions through substitution over time and across choices.

We first discuss the intertemporal substitution, which is the key to the stimulus objective. A one-period temporary scrappage subsidy reduces the cost of purchasing a new eligible vehicle, thus rasing the log-inclusive value in the current period relative to that in the future periods. In a dynamic model setting, the household takes the comparison of the maximum purchase options into account. A temporary subsidy encourages households to pull demand from the future to the current period. The extent of substitution depends upon the price sensitivity parameter α, the current and expected household income and vehicle prices, as well as the comparison of vehicle characteristics and fuel expenditure of the currently owned vehicle and the eligible vehicle to be purchased.

In terms of substitution across vehicle choices, specifications on eligible trade-in and new vehicles not only determine owners of what vehicles can enjoy the subsidies, but also influence their choices of new vehicles to purchase. The household may balance the utility gain of driving a vehicle with desirable characteristics, in terms of horsepower and weight, against the cost of paying for both new vehicles and future fuel expenses. When scrappage subsidies depend positively on the differences between the fuel economy of new and trade-in vehicles, not only does the relative value of scrapping eligible "clunkers" increase, but the cost of purchasing vehicles of higher fuel economy decreases as well. The extent of substitution across vehicles of different fuel economy, however, depends upon the household's preferences for certain vehicle characteristics, such as horsepower and weight, that are closely related to its fuel efficiency. If a household is strongly averse to fuel efficient vehicles (e.g., due to strong preference for horsepower and weight), more generous scrappage subsidies are needed to alter its decision.

The scrappage subsidies, if properly designed, may encourage the scrappage of "clunkers" and the purchase of new fuel efficient vehicles. The effectiveness of the subsidy program in achieving stimulus and environmental objectives, however, depends upon the underlying structural parameters.

3.4.2 Aggregate Implications

In this section, we characterize the evolution of the cross-sectional distribution of vehicles and vehicle ownership. Given the initial distribution of vehicle ownership, vehicle characteristics, heterogeneous preferences and income across households, our model can generate new vehicle sales by model and the distribution of vehicle stock over time based on households' optimal scrappage and purchase decisions. The new vehicle sales and the evolution of vehicle stock distribution are then used in both the structural estimation and counterfactual experiments as well.

Let n_{ikt} denote the fraction of households of type i that own vehicle model k at the end of period t. Since households are heterogenous with respect to preferences for owning vehicles per se (the constant term), preferences for vehicle weight (the weight coefficient) and the idiosyncratic income, we use $\Gamma(\zeta_i)$ to represent the distribution of households across the three heterogeneous features. Here ζ_i is a three-dimensional vector representing the three aspects of heterogeneity.

Let n_{jt}^{new} denote the total purchases of model j in period t, which is an integrated sum of purchases of model j by individual household i. Given the purchase probabilities derived above, we have

$$n_{jt}^{new} =_{\zeta_i} \sum_{k\in\{\mathcal{J}_{t-1},0\}} \mu_i^{kj}(\phi_{ikt}, \delta_{it}, \mathbf{S}_t)\, n_{ikt-1} d\Gamma(\zeta_i). \tag{16}$$

Similarly, let n_{kt}^{pre} denote the proportion of households holding a durable good k from period $t-1$ to t, we have

$$n_{kt}^{pre} =_{\zeta_i} \mu_i^{kk}(\phi_{ikt}, \delta_{it}, \mathbf{S}_t)\, n_{ikt-1} d\Gamma(\zeta_i). \tag{17}$$

Hence the total proportion of households holding vehicle model j at the end of period t is $n_{jt} = n_{jt}^{new} + n_{jt}^{pre}$. The terms within the integral sign in equations (16) and (17) are the fraction of households of type i who purchases vehicle j or holds onto their pre-owner vehicle k. Accordingly, the fraction of households of type i that own vehicle model j at the end of period t is

$$n_{ijt} = n_{ijt}^{new} + n_{ijt}^{pre}. \tag{18}$$

The distribution of vehicle stock evolves over time as a result of vehicle ownership decisions made by households.

Intuitively, vehicle owners make decisions regarding whether to sell their current vehicle or keep it partly based on the prices of all new and used vehicles. Their decisions then generate the supply for the used vehicles. At the same time, vehicle owners as well as non-vehicle owners decide whether to buy a vehicle and if so what to buy (it could be used or new). Their decisions in turn generate the demand for the used vehicles (and new vehicles). The difference between the supply and demand for a used-vehicle model is treated as scrappage, which affects the evolvement of the vehicle stock.

4 Econometric Implementation

In this section, we describe our empirical strategy. We set the discount rate β to be 0.95 and divide the other parameters into two sets. The first set of parameters are either calibrated or estimated outside of the dynamic model. The second set of parameters are the preference parameters and are the focus of our paper. They are estimated using the simulated GMM where the moment conditions are constructed based on vehicle attributes and prediction errors in vehicle sales and stock. We now describe the calibration and estimation of these two sets of parameters in detail.

4.1 Pre-Calibrated or Pre-Estimated Parameters

The set of parameters which are pre-calibrated or pre-estimated outside the structural model include the following three categories: (1) those governing the exogenous processes of average household income and gasoline prices $\{Y_t, O_t\}$, the aggregate state variables; (2) those governing the dependence of vehicle miles of travel upon vehicle characteristics such as fuel economy, age, and vehicle type; and (3) those governing the depreciation of vehicle prices over time as a function of vehicle characteristics.

4.1.1 Transition Dynamics of Aggregate State Variables

We specify the stochastic processes for the two aggregate state variables, the average household income and the gasoline price, as a VAR(1) process.

$$\begin{bmatrix} Y_t \\ O_t \end{bmatrix} = \begin{bmatrix} \varkappa_Y \\ \varkappa_o \end{bmatrix} + \begin{bmatrix} \rho_{yy} & \rho_{yo} \\ \rho_{oy} & \rho_{oo} \end{bmatrix} \begin{bmatrix} Y_{t-1} \\ O_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{Yt} \\ \varepsilon_{ot} \end{bmatrix}, \tag{19}$$

where the mean of the error terms are zero and the covariance matrix of the error terms is given by:

$$\Sigma = \begin{bmatrix} \omega_{yy} & \omega_{yo} \\ \omega_{oy} & \omega_{oo} \end{bmatrix}. \tag{20}$$

Since these processes are exogenous to the household, we estimate the VAR(1) parameters outside of the dynamic optimization problem in order to reduce the computational burden. Based on the data on average household income and gasoline prices from 1967 to 2012, we estimate a VAR(1) process for these variables after removing the trend using a quadratic function. The parameter estimates are presented in Table 2. Most of the parameters are estimated precisely and have intuitive signs.

4.1.2 Parameters Determining Vehicle Miles of Travel

In making vehicle purchase decisions, households need to factor in both the capital cost for vehicle purchases but also future fuel costs. The gasoline expenditure per vehicle is equal to vehicle miles of travel (VMT) in a given period multiplied by the gasoline cost per mile. While the latter is the product of gasoline prices and the fuel efficiency in terms of gallons per mile), vehicle miles of travel are considered as reflecting vehicle usage decisions. Goldberg (1998) and Bento et al. (2009) model vehicle choices and usage as joint decisions. Since our research focuses on vehicle choice decisions, in order to reduce the computational burden, we estimate preference parameters that govern decisions on vehicle choices inside the dynamic structural model, but estimate the parameters that govern vehicle usage decisions outside of the dynamic model. It is well documented in the literature that VMT vary across vehicle type (cars and light trucks), age, and fuel efficiency and it is also affected by gasoline prices. To parsimoniously capture the dependence of VMT on vehicle attributes and gasoline prices, we assume that VMT for a given vehicle k in period t is an exponential function of the gasoline cost per mile, that is,

$$VMT_k = \vartheta\left(a_k, g_k\right)\left(O_t e_k\right)^{\eta}, \tag{21}$$

where , $O_t e_k$ represents the gasoline cost per mile, which is the product of gasoline prices O_t and the fuel efficiency of vehicle k, e_k,in terms of gallons per mile. The coefficient $\vartheta\left(a_k, g_k\right)$ is specific to the age and type of the vehicle, and the exponent η represents the elasticity of mileage with respect to the fuel cost (i.e., the rebound effect). As a result, $f\left(g_k, e_k, O_t\right)$, the total gasoline expenses for driving a vehicle with characteristics $\{a_k, g_k, e_k\}$, is given by $\vartheta\left(a_k, g_k\right)\left(O_t e_k\right)^{\eta+1}$.

The parameters in equation (21) are well studied in the literature. Using U.S. state-level annual data from 1997 to 2001, Small and Van Dender (2007) estimate the short-run rebound effect to be -0.022, which we adopt as the value for η.

We assume that $\vartheta\left(a_k, g_k\right)$ takes the following form:

$$\vartheta\left(a_k, g_k\right) = \vartheta_{1,g_k} a_k^{\vartheta_{2,g_k}}. \tag{22}$$

Given gasoline cost per mile, the parameters ϑ_{1,g_k} and ϑ_{2,g_k} determine vehicle miles of travel for any given vehicle types and ages. We use $g_k = 1$ to indicate vehicle type as car, and $g_k = 2$ to indicate light trucks. Based on household-level data from the National Household Travel Survey (2001), Lu (2006) documents that vehicles are used less as they age and that light trucks register more mileage than cars. We estimate these two pairs of parameters based on the VMT data by vehicle type and age from Lu (2006):

$$\vartheta_{1,1} = 1.8, \vartheta_{1,2} = 2.1, \vartheta_{2,1} = -0.29, \vartheta_{2,2} = -0.31.$$

4.1.3 Price Depreciation of Used Vehicles

Following Schiraldi (2011), a vehicle owner pays the rental price of the vehicle for the given period. The rental price is defined as the different between the current price and the discounted (expected) price in the next period. To calculate the rental price, we estimate a price depreciation schedule for used vehicles following this specification:

$$P_{ja} = P_{j0} \exp(x_j \kappa + \varsigma_j), \tag{23}$$

where P_{ja} is the price of model j at age a while P_{j0} is the price when the vehicle was new. x_j includes vehicle age and its interactions with vehicle attributes while ς_j captures idiosyncratic shocks. To estimate this equation, we obtain used vehicle prices in 2000 and 2008 from IHS Automotive and construct a price depreciation variable based on these prices for used vehicles and the prices when these vehicles were new. We transform the model into a linear model and define the dependent variable as $\log(P_{ja}/P_{j0})$.

Table 3 presents the parameter estimates. The model has a good fit with an adjusted R^2 of 0.946. The estimation shows that prices depreciate with age but the depreciation is slower among luxury vehicles (relative to non-luxury vehicles), trucks (relative to cars), vehicles produced by European automakers, Japanese Big Three (Honda, Nissan, and Toyota), and the Big Three (relative to those produced by other Asian automakers). The interaction term between age and MSRP has a negative coefficient suggesting that more expensive vehicles depreciate faster holding constant other variables such as the luxury dummy designation. With these parameter estimates, we can interpolate the prices for used vehicles based on MSRPs and vehicle attributes in our estimation of the dynamic model and counterfactual simulations.

4.1.4 Unobserved product attributes

We incorporate several vehicle attributes in the utility function including vehicle type, fuel efficiency, vehicle weight, and horsepower. It is likely that consumers also value attributes that we do not have in the data such as style and quality. To deal with unobserved product attributes, both Gowrisankaran and Rysman (2012) and Schiraldi (2011) follow the strategy in Berry, Levinsohn and Pakes (1995) which matches market shares observed in the data and those predicted by the model to back out the unobserved product attributes. They embed a contraction mapping technique to recover the unobserved product attributes inside of the value function iteration. Given that we have four state variables (the logit-inclusive value, flow utility, and two aggregate state variables) instead of two state variables as in Gowrisankaran and Rysman (2012) and Schiraldi (2011), this approach to deal with unobserved attributes would render the estimation computational impractical in our context.

Instead, we adopt the control function approach by Petrin and Train (2010) which tries to recover the unobserved attributes using the hedonic price regression. Using vehicle models sold from 1974 to 2012, we regress vehicle prices on a set of vehicle attributes and then recover the residuals. We take the residual as unobserved attributes and include their 2nd-order polynomials in the utility function in the dynamic demand estimation. The weakness of the control function approach is that our model would not be able to predict the sales data perfectly as the contraction mapping method would.

Table 4 presents the coefficient estimates of the hedonic price function. The model has a good fit with an R^2 of 0.929. The coefficient estimates on vehicle attributes are intuitively signed. Prices increase with vehicle weight and horsepower in the observed range of weight and horsepower. Price decreases with fuel consumption measured in gasoline consumption per 100 miles for all light trucks and over 95 percent of the car models. We treat the exponential value of the residuals and its second-order polynomial as unobserved attributes in the utility function. The range of the unobserved attributes is from 0.47 to 16.33. Its correlation coefficient with vehicle price is 0.247.

4.2 Estimation of Key Parameters

The focus of our estimation strategy is the parameters in the contemporaneous utility function, including preference parameters for vehicle attributes, the distribution parameters of random coefficients that capture the dispersion of the preference heterogeneity, and the transaction cost parameter. We include random coefficients on the constant term and on vehicle weight. The estimation is based on the cross-sectional distribution of vehicle stock (i.e., vehicle registration data) at the vintage-nameplate (i.e., model) level in 2000, 2005 and 2008, as well as new vehicle registration data from 2000 to 2008. The estimation strategy is to find the parameter vector through the simulated GMM, where moment conditions are constructed based on observed vehicle attributes and differences between observed vehicle registration data to their simulated counterparts (e.g., the prediction errors).

The simulated GMM includes two sets of moment conditions. The first set of moment conditions are based on new vehicle sales from 2001 to 2009 while the second set are based on vehicle stock in 2000, 2005 and 2008. Conditional on the state variables, pre-calibrated and pre-estimated parameters, and a given set of key parameters, our framework can generate demand for new vehicle models. We match the demand for new vehicle models to the observed sales data from 2001 to 2008 and generate prediction errors. The first set of moment condition assumes that the observed vehicle attributes are not correlated with the prediction errors.

Similarly, our framework can generate predictions of annual vehicle survival for used vehicles. For a given used-vehicle model, the annual survival rate is determined by the decision to keep the vehicle among existing owners of this particular model and the decision to purchase the vehicle by those who currently do not own this particular model. Given the registration data in 2000, those survival rates lead to predictions of remaining registration in 2005 for each model. Similarly, the registration data in 2005 can be used as a starting point to predict the remaining registration in 2008. The second set of moment conditions is based on the assumption that the observed vehicle attributes are not correlated with the difference between the observed vehicle stock data (in 2005 and 2008) with their predicted counterparts.

Here we denote the parameters in the utility function as θ_1, and denote those governing the AR(1) processes of the log inclusive value δ and the flow utility ϕ, defined in equations (11) and (12), as θ_2. The AR(1) processes defined by θ_2 are different across households with different income and unobserved preferences.

Based on the simulated and observed data on new vehicle sales, the first set of moment conditions, M_1, are constructed following the assumption:

$$\mathrm{E}\Big[(\hat{q}_j^n(\theta_1, \theta_2) - q_j^n)|x_j^n\Big] = 0,$$

where $\hat{q}_j^n(\theta_1, \theta_2)$ represents predicted new vehicle sales of model j and q_j^n represents observed sales from 2001 to 2008. Here we use the superscript "n" to represent "new" vehicle sales. The vector, x_j^n, denotes a set of observed vehicle attributes including weight, horsepower, fuel economy and vintage. The second set of moment conditions, M_2, are set up based on the simulated and observed data on used vehicle stock under the following assumption:

$$\mathrm{E}\Big[(\hat{q}_j^u(\theta_1,\theta_2) - q_j^u)|x_j^u\Big] = 0,$$

where $\hat{q}_j^u(\theta_1,\theta_2)$ represents predicted vehicle stock of used model j and q_j^u denotes observed stock in either 2005 or 2008. Here we use the superscript "u" to represent "used" vehicle stock and x_j^u represents corresponding vehicle attributes.

The two sets of moment conditions are stacked together. The GMM estimators $\hat{\theta_1}, \hat{\theta_2}$ minimizes:

$$M(\theta_1,\theta_2)'WM(\theta_1,\theta_2) = \begin{pmatrix} M_1(\theta_1,\theta_2) \\ M_2(\theta_1,\theta_2) \end{pmatrix}' \begin{pmatrix} W_1 & 0 \\ 0 & W_2 \end{pmatrix} \begin{pmatrix} M_1(\theta_1,\theta_2) \\ M_2(\theta_1,\theta_2) \end{pmatrix}.$$

The procedure involves iteratively updating θ_1 and θ_2 to minimize the objective function. We start with using the identity matrix as the weighting matrix W to obtain consistent initial estimates of the parameters and optimal weighting matrix. We then estimate the model using the new weighting matrix.

The estimation procedure can be closed with an additional assumption. The number of non-vehicle owners in 2000 is set to be 10 percent of the U.S. households.[8] In each period, the pool of non-vehicle owners is updated taking into count: (1) some vehicle owners become non-owners by scrapping their vehicles; and (2) some non-owners choose to buy a new vehicle and become a vehicle owner.

5 Estimation Results

In this section, we discuss estimates of the key parameters in the structural model. We then use these parameter estimates to conduct quantitative analysis and examine their implications on household choices.

5.1 Parameter Estimates

Before presenting parameter estimates from the structural model, we first present estimation results from the reduced-form OLS regressions of vehicle scrappage rates on vehicle age and fuel economy. We perform the regressions separately for the 5-year scrappage rate from 2001 to 2005 and the 3-year scrappage rate from 2006 to 2008. The regression results provide guidance on

[8]The percent of U.S. households without a vehicle was 9.4 and 9.1 percent in 2000 and 2010, respectively. We perform robustness checks on this assumption and find that our findings are robust.

our modeling strategy of the structural estimation and help us interpret the estimation results from the structural estimation.

Panel 1 of Table 5 presents the results for two regressions where the first one controls for make fixed effects and the second one does not. The dependent variable is the 5-year scrappage rate by vintage-nameplate from 2001 to 2005. The explanatory variables include gpm in logarithm, vehicle age in logarithm, and their interactions with car dummy. In both regressions, a larger gpm (lower fuel economy) is associated with a smaller scrappage rate and the correlation is stronger for cars. Since we do not control for variable attributes such as vehicle size, horsepower and weight, this correlation between fuel efficiency and scrappage rate captures the effects of these vehicle attributes on scrappage. Not surprisingly, vehicle age is positively correlated with vehicle scrappage. The R^2 is 0.729 and 0.781 in the two regressions. Panel 2 of Table 5 shows the results for the 3-year scrappage rate from 2006 to 2008. The results are qualitatively similar to those in panel 1. In both panels, the coefficients on interactions terms containing the car dummy are all statistically significantly different from zero. In the structural model, we allow different parameters for these two types of vehicles as well.

We now turn to estimates of the key parameters in the utility function as specified in equations (2) and (1). Table 6 presents coefficient estimates and their standard errors for three specifications.[9] The first specification has no consumer heterogeneity in preferences other than the heterogeneous price sensitivity to the user cost of a vehicle (depreciation plus the fuel cost in a given year) due to the idiosyncratic component of household income. The second specification adds random coefficients on consumer preference for owning a vehicle and for vehicle weight but does not control for unobserved vehicle attributes. We assume that the heterogeneous coefficients on both the constant and the vehicle weight have a normal distribution and estimate their means and standard deviations. The last specification includes both random coefficients and unobserved vehicle attributes.

Most of the coefficient estimates are intuitively signed and statistically significant. The first coefficient, α, captures the price sensitivity of households to the user cost of a vehicle. We scale α by the reciprocal of the household's individual income to capture the negative effect of income on consumer price sensitivity. In the second specification where unobserved product attributes are not controlled for, the estimated value of α is much smaller than that from the last specification. The comparison is consistent with the finding in the demand literature that ignoring unobserved product attributes would bias the price coefficient toward zero. Signs of

[9] The parameter estimates are based on simulated GMM using 100 randomized Halton draws. The results using 75 Randomize Halton draws are similar. We discretize the state space of the four state variables, logit-inclusive value δ, flow utility ϕ, average household income and gasoline prices, into 20, 6, 6, and 6 grids respectively.

coefficient estimates on age, horsepower and weight are as expected. The coefficient estimates on unobserved attributes in both Specifications one and three are positive and significant. The estimated standard deviations of random coefficients on the constant and the vehicle weight, when compared with their respective means, suggest significant consumer heterogeneity in preference for both vehicle ownership and vehicle weight.

The coefficient estimate for the transaction cost is significant in all specifications. Based on the last specification, the monetary value for the transaction cost (assuming an income level of $55,000) amounts to about $2200. This is somewhat smaller than the estimate of 2000 Euro in 2004 from Schiraldi (2011) for Italy. The discrepancy could be a reflection of different amounts of frictions in the two automobile markets. The implied transaction cost in Specification two is $10,250, much higher than that implied from Specification 3. As the price sensitivity is lower in the second specification which does not control for unobserved product attributes, the transaction cost is biased upward to depress vehicle demand in order to better fit the data on vehicle transactions.

5.2 Model Fit and Quantitative Analysis

In this section, we conduct simulations to generate model predictions using parameter estimates. The goal is to examine the implications of the estimates on household choices and gauge whether the estimates can capture some salient features of the data.

First, we examine model predictions for new vehicle sales. Figure 4 plots observed and predicted new vehicle sales for cars in the top panel and light trucks in the bottom panel from 2001 to 2008. The predictions seem to track the observed sales reasonably well. There are two features worth noting. First, the predictions have larger variations over time than those exhibited in the observed sales data pre-2007. This may be driven by the over-reliance on changes in household income and gasoline prices in capturing the fluctuation in vehicle sales. Second, although our model predicts a drop in vehicle sales in 2007 and 2008 but the drop was not as sharp as observed ones. The reduction in vehicle sales during the recent economic recession was partly driven by tighter credit access and drop in consumer confidence, neither of which are captured in our model.

Figure 5 plots survival rates of passenger cars and light trucks by age, both observed in the data and predicted by our model. The plots are based on parameter estimates of Specification 3 in Table 6, which allows for both preference heterogeneity and unobservable vehicle attributes. Other specifications yield similar predictions. The top graph shows observed and predicted 5-year survival rates from 2001 to 2005 by vehicle type and age and the bottom graph depicts

3-year survival rates from 2006 to 2008. As shown in the figure, the simulated survival rates of both passenger cars and light trucks diminish as vehicles age, with light trucks having higher survival rates than cars. Both features are consistent with the observed data. Furthermore, the simulated survival rates match the observed rates quite well especially for vehicles less than 15 years old. That the match not being as good for older vehicles is likely driven by larger variations in observed survival rates from fewer registrations per model.

To illustrate the importance of dynamics in the market, we examine the sales impact of a temporary price change and that of a permanent price change. In a static demand model where consumer decisions do not have dynamic consequences, a temporary price change would generate the same responses as a permanent price change of the same magnitude. However, due to the durable-good nature of vehicles and the existence of transaction costs in this market as shown in parameter estimates, these two types of price changes could generate different responses in sales.

We examine the impact on new vehicle sales from a one-percent temporary price increase in 2003 and a one-percent permanent price increase imposed on all new vehicle from 2003 onward. The price shock is unexpected before 2003 in both cases and households know the nature of the price increase. In the simulations, we assume that the stochastic processes governing the evolution of the log-inclusive value δ and the flow utility ϕ are not altered by the shocks. For temporary shocks, we assume that the logit-inclusive value of the next period is based on the logit-inclusive value in the current period under a scenario of no shocks. For permanent shocks, the logit-inclusive value in the next period is based on realized value in the current period with shocks.

Figure 6 depicts the impact on new vehicle sales under the two price shocks.The results show that the temporary price increase would reduce sales more than the permanent price increase in 2003: with a temporary price change, some consumers postpone their purchase from 2003 to later years resulting a larger drop in sales and visible increase in sales in several future years. Gowrisankaran and Rysman (2012) present a similar finding in the context of camcorders. The comparison from this figure shows the importance of incorporating dynamics in the model, especially given that our focus is to examine the short- and long-run impacts of a temporary subsidy policy.

6 Policy Analysis

In this section, we conduct policy analysis for nine different designs of CFC programs based on our parameter estimates to analyze the cost-effectiveness of different designs. The goal is to understand how various eligibility rules, especially those that are designed for environmental considerations, affect both stimulus and environmental outcomes of the CFC-type programs.

6.1 Setting the Stage

As described in Section 2.1, the CFC program lasted for about a month in 2009. Because the decision horizon in our model is one year, we choose to implement a hypothetical program with the same key eligibility rules as the CFCs, but with a duration of one year in 2009. Since our focus is on the comparison of various policy designs under the same outside environment, as long as the duration of the program does not favor one program over the other, our policy comparisons remain valid.

We define the CFC-type policy for a one-year duration as our benchmark policy, as opposed to alternative polices examined below with different eligibility rules. To be eligible for the subsidy, the following requirements have to be met under the benchmark policy:

(1) For trade-in vehicles, the maximum age is 25 and the maximum mpg is 18.

(2) For new vehicles, the minimum mpg is 22 for a passenger car, and 18 for a light truck;

(3) The mpg improvement for a new car over the trade-in vehicle has to be at least 10 to qualify for \$4500, and four to qualify for \$3500. The cutoff points are five and two for a new light truck.

The eligibility requirement on the age of the trade-in vehicles could screen out those households who would purchase a new vehicle in the absence of the program (e.g., inframarginal consumers), while the other rules on mpg for both trade-in and new vehicles are designed to achieve better environmental outcomes. It is important to note that a CFC program without the mpg requirements could still achieve better environmental outcomes than without the program, since new vehicles tend to be cleaner than used vehicles[10] There is one minor difference between the above rules and those in the real CFC program. For all light trucks, we adopt the

[10] This point is argued by Alan Blinder in his New York Times article and confirmed by our simulations below. Indeed, the CFC program outlined in his article does not include requirements on new vehicles, although he suggested similar eligibility rules for trade-in vehicles.

requirements for category one trucks as in the real CFC program. That is, we do not have the distinction for different categories because our dynamic model does not capture that.[11]

In conducting the simulations, We assume that the program is implemented in 2009 and unexpected to households. Once unveiled in the beginning of 2009, households know that the program will only last for a year. We start with the observed vehicle population profile in 2008 and simulate changes in vehicle population through new vehicle sales and scrappage from 2009 onward till 2033. For years between 2009 and 2012, we use the observed average household income, gasoline prices, and choices of vehicle models. For years after 2012, we use the steady-state values for those state variables. We assume that the policy does not affect the underlying stochastic processes governing the evolution of the log-inclusive value δ and the flow utility ϕ.

When deciding whether to participate in the program, a household would compare the subsidy that it would get against the scrap value and the potential loss in consumer surplus if the optimal choices with and without the program are different (e.g., the program leads to a suboptimal choice for the consumer). We equate the scrap value of a vehicle to its price as a used vehicle. As shown in Section 4, the scrappage value depends on vehicle attributes.

To facilitate the comparison across different policy scenarios, we adjust the level of subsidy under all alternative policies so that the total spending would be the same as the level under the benchmark policy. This amounts to the assumption that the government has a fixed budget for the CFC program. The evolution of cross-sectional vehicle distribution over time allows us to examine program impacts on stimulus outcomes and environmental benefits.

We evaluate the effectiveness of the program in terms of stimulus based on two criteria: vehicle sales and household spending on vehicles induced by the program. New vehicle sales are often used to measure the demand stimulus in the policy discussion and in the previous literature such as Mian and Sufi (2011), Copeland and Kahn (2012), and Li et al. (2013). Household spending, determined by both program-induced sales and the prices of those vehicles (minus the total subsidy), is a more accurate measure of the monetary value of the demand stimulus. Depending on prices of the program-induced vehicle sales, different program designs could rank differently based on these two measures.

The environmental benefits are measured in two parts. The first part measures benefits from reductions in CO_2 emissions. We calculate gasoline consumption and CO_2 emissions under

[11]Category 1 trucks include SUVs with gross vehicle weight no more than 10,000 lbs, pickup trucks with gross vehicle weight no more than 8500 lbs and wheelbase no more than 115 inch, and passenger vans and cargo vans with gross vehicle weight no more than 8500 lbs and wheelbase no more than 124 inch. All SUVs except the large SUVs, all minivans, and small pickup trucks are category 1 trucks. In alternative simulations, we adopt the requirement for category 2 truck and find qualitatively the same results.

various scenarios based on the simulated fleet characteristics and VMT. We follow the VMT schedule over a vehicle's lifetime based on Lu (2006), which shows declines in annual VMT for passenger cars and light trucks as vehicles age. The average lifetime VMT is estimated at 152,137 for a car and 179,954 for a light truck. The benefits from reductions in CO_2 emissions are monetized based on the social cost of carbon (social marginal damages) estimated by the United States Government Interagency Working Group (2010). Based on three integrated assessment models, the Working Group provides a range of \$5 to \$65 per ton for 2010 emissions (in 2007 dollars) with a central value of \$21 at a discount rate of 3 percent. The social cost increases to \$36 dollars (in 2007 value) by 2035.

The second part of the environmental benefits comes from reductions in criteria pollutants including carbon monoxide, volatile organic compounds, nitrogen oxides, and exhaust PM2.5. The emissions of these pollutants per mile of travel for trade-in vehicles are from MOBILE6, a program maintained by the EPA that calculates emission factors for different types of vehicles. The model takes into account the fact that as a vehicle ages, the emissions level per unit of travel can increase dramatically, especially for older vehicles. To translate changes in these emissions into monetary terms, we assume that the average damage per ton of the four pollutants is \$74.5, \$180, \$250, and \$1,170, respectively. The average cost for carbon monoxide is the average of the range reported by McCubbin and Delucchi (1994). The other three cost parameters are the median marginal damages from Muller and Mendelsohn (2009).

Since there is significant uncertainty in the literature regarding the social cost of carbon and other pollutants, we double the numbers cited above in a robustness check and our qualitative findings remain. This is largely driven by the fact that the environmental benefits turn out to be much smaller than the cost of the program, which is measured by the total subsidy of the program and the lost value of trade-in vehicles from physical scrappage.

6.2 Simulation Results

Table 7 presents the simulation results for nine scenarios. The results are presented as relative to the outcomes from a scenario of no subsidy which we simulate first. Scenario 1 is the benchmark policy, a design that largely follows the real program. Scenarios 2 to 8 all have different eligibility rules to examine the effect of various requirements on new and trade-in vehicles. Scenario 8 is a program without any specific eligibility rules as long as a household trades in a used-vehicle for scrappage and then buy a new vehicle. Scenario 9 has the same design as the benchmark policy but we adjust the average household income and gasoline prices in 2009 to be those observed in 2007 to examine to what extent the program outcomes are affected by macroeconomic conditions.

The metric that we use to make comparisons is given by the last two columns. Cost per unit of vehicle sales is the net cost per unit of program-induced vehicle sales where the net cost is calculated as the total subsidy plus the scrap value of trade-in vehicles minus the environmental benefits. Cost per dollar of spending is the net cost per dollar of program-induced consumer spending, which is calculated as the total spending on program-induced sales minus the total subsidy. The total amount of subsidy under scenarios 1-8 is $20.56 billion while that under scenario 9 is $19.90 billon.

Outcomes under Benchmark Policy Under the benchmark policy, the number of eligible transactions would be 4.787 million with an average subsidy of $4300 for each eligible transaction. Among these eligible transactions, 3.379 million (or 71 percent) would not have happened without the program, i.e., program-induced sales. Total consumer spending from these program-induced sales amounts to $48.35 billion. These induced sales and spending represent the true stimulus effect on vehicle demand in 2009. The outcomes under the hypothetical benchmark policy seem plausible in comparison with observed outcomes from the CFC program actually implemented in 2009. In the one-month run of the CFC program, $2.85 billion was spent on $680,000 transactions with an average subsidy of $4,200 based on the transaction data from the program. Therefore, the total subsidy and eligible transactions under the one-year program are about seven times as large as those under the one-month program in reality.

The total scrap value of the trade-in vehicles is 7.762 billion, implying an average scrap value of $1,600 per eligible transaction. This represents the lost value from the scrappage of the trade-in vehicles, a significant amount relative to the total subsidy. The environmental benefits, the discounted sum over the next 25 years from reduced CO_2 and four criteria pollutants as discussed above, are valued only at $0.16 billion (relative to the no-policy scenario). The net cost per induced sales is $8,336, compared to the average price of $20,400 for the induced sales. The net cost per dollar of induced consumer spending is $0.583, implying that 58 cents of subsidy is required from the government in order to induce one dollar of spending by households under the program.

Outcomes under Alternative Designs In Scenario 2 we consider a policy that provides the same amount of subsidy to all eligible transactions, rather than using the two-tier design in scenario 1. The two-tiered subsidy, which offers differential amounts of rewards based on the difference in fuel efficiency of the trade-in and new vehicles, is designed to encourages households to buy more fuel-efficient vehicles for the goal of larger environmental benefits. As compared to Scenario 2, the benchmark two-tier design results in slightly more induced-sales but less consumer spending: implying that vehicles sold under the two-tier design are slightly cheaper. By and large, these two designs lead to very similar outcomes.

In Scenario 3 we remove the mpg requirement on trade-in vehicles, which aims to enhance the environmental outcome by taking fuel inefficient vehicles off the road. Despite its environmental focus, we find that eliminating this requirement reduces the environmental benefit only slightly, but significantly increases induced-sales and consumer spending. Removing this requirement expands the pool of eligible buyers and results in more eligible transactions and induced sales. The net result is a large reduction in the two cost measures. Indeed, the design presented in scenario 3 is the most cost-effective based on the metric of consumer spending. The unit cost in terms of consumer spending under the benchmark policy is 43 percent higher than that in this design. The gap in the unit cost shows that the pursuit of environmental objectives by restricting the mpg of trade-in vehicles conflicts with the goal of cost-effective stimulus.

In Scenario 4 we continue to impose no mpg requirements on trade-in vehicles, but increase the mpg requirement on new vehicles from 22 and 18 for cars and trucks to 24 and 19 (the median of the mpg distributions) respectively. This design helps with the environmental outcome and also increases the sales but not consumer spending. Relative to scenario 3, scenario 4 performs better in the metric of vehicle sales but not consumer spending. These simulation results suggest that the mpg requirement on new vehicles does more than just affecting the environmental outcomes. The requirement also alters the pool of eligible consumers and hence the stimulus outcomes. Nevertheless, its effect on the environmental dimension is rather limited.

In Scenario 5-6, instead of imposing mpg requirements on new vehicle, we impose maximum MSRPs as an eligibility requirement on new vehicles. The results suggest that restricting MSRPs can improve program effectiveness in terms of sales but not consumer spending. The unit cost in terms of induced sales under the benchmark policy is 37 percent higher than that in scenario 6. By focusing on vehicle with lower prices, the program can better target consumers with lower income who are likely to be more sensitive to prices and hence subsidy. Thus the total spending by these consumers could be lower even with a larger sales. These two scenarios show that cost savings comes from better targeting of marginal consumers, rather than environmental elements.

In scenario 7, we remove the age requirement on trade-in vehicles which aims to limit inframarginal consumers. The comparison with scenario 6 suggests that the age requirement improves the cost-effectiveness in both metrics. Scenario 8 removes all requirements on new and used vehicles as was original proposed by Alan Blinder in his New York Times article. Comparing with the benchmark policy, it has a smaller though positive environmental impact. It performs marginally better in terms of cost per induced sales but in terms of consumer spending, it is much more effective.

The last scenario has the same design as scenario 1 but assumes that households in 2009 face the average household income and the gasoline prices observed in 2007. The results do not differ dramatically from the outcomes in scenario 1. Similarly, we also conduct the simulations for the other scenarios and obtain very similar results as well. These findings suggest that the outcomes observed from the benchmark policy are not likely to be driven by the specific macroeconomic conditions during 2009.

In all those scenarios the monetized environmental benefits only make up for a small portion of total subsidies. The dramatic contrast in magnitude indicates that even in cases where environmental gains are truly co-benefits, the gain can be too small and easily dominated by the loss of foregoing an alternative design that targets marginal consumers better.

Figure 7 shows the long-run impacts on sales and environment benefits for scenarios 1, 3 and 6. To ease exposition, the outcomes in the no-policy scenario are normalized to zero and only differences across policy scenarios are shown. The design in scenario 3 has the best cost-effectiveness in terms of vehicle sales while that in scenario 6 in terms of consumer spending among scenarios 1-8. The top panel shows that the CFC program under all three scenarios increase vehicle sales with scenarios 3 and 6 seeing stronger impacts than the benchmark policy. Some of the induced sales observed in 2009 are a result of consumers pulling their demand forward, as intended by the program. The bottom panel shows that while all three designs have a positive impact on the environment as a result of reduced emissions, the benchmark policy generates the largest environmental benefits.

The comparison in Figure 7 highlights the potential tension between the environmental and the stimulus objectives. The CFC program as implemented achieves marginally better environmental outcomes at the expense of costly demand stimulus. The key eligibility requirement that leads to this tradeoff is the maximum mpg requirement on trade-in vehicles. Nevertheless, the two objectives are not always at odds with each other. The comparison between scenarios 3 and 8 suggests that some of the design elements may enhance both objectives. Although the goal of our analysis is not to pinpoint the optimal locus in the space of design parameters, our analysis illustrate that the key to a successful program is to first understand the potential tradeoff between these two objectives. The design of such a program should focus on better targeting of marginal consumers and maximizing the stimulus objective.

7 Conclusion

In the context of the popular Cash-for-Clunkers program in the U.S., we provide the first empirical study to examine the potential tradeoff between the stimulus and environmental objectives. We use detailed national vehicle registration data to estimate a dynamic discrete choice model of vehicle ownership and conduct counterfactual simulations with alternative policy designs. Our results highlight that the design elements for the environmental objective can significantly undermine program effectiveness on stimulus, implying that there could be a significant tradeoff between the two objectives. This finding should serve not only as a reminder of Tinbergen's rule on efficient policy design with multiple objectives, but also as a caution that green stimulus programs similar to the CFCs should not substitute for sound environmental policies such as the Pigouvian tax.

The silver lining of our analysis is that the stimulus and environmental objectives are not always diametrically opposed. By better targeting marginal consumers, some design elements on new and trade-in vehicles could enhance both objectives. Future research could try to pinpoint the optimal locus in the space of eligibility rules based on vehicle attributes or consumer demographics with richer household-level data. Our findings illustrate that to improve cost-effectiveness in a CFC-type program, it is important to recognize and understand the potential tradeoff between the stimulus and environmental objectives.

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Table 1: Vehicle Population Profile and New Vehicle Sales

Variable	Mean	S.D.	Min	Max
Panel 1: 2000 Vehicle Profile				
Vehicle age	8.65	5.55	1	27
Car dummy	0.63	0.48	0	1
mpg	21.08	4.66	9.80	55.14
Weight (1000lbs)	3.41	0.88	1.49	9.30
Vehicle horsepower	152	60	46	552
No. of registrations	23807	43846	2	432297
Panel 2: 2005 Vehicle Profile				
Vehicle age	9.43	5.99	1	32
Car dummy	0.58	0.49	0	1
mpg	21.02	4.72	9.81	63.96
Weight (1000lbs)	3.55	0.93	1.49	9.30
Vehicle horsepower	170	70	46	605
No. of registrations	21696	41100	2	433049
Panel 3: 2008 Vehicle Profile				
Vehicle age	9.75	6.46	1	35
Car dummy	0.55	0.50	0	1
mpg	21.28	5.08	9.81	63.96
Weight (1000lbs)	3.65	0.94	1.49	9.30
Vehicle horsepower	181	76	46	605
No. of registrations	19692	38462	1	663667
Panel 4: New Vehicles 2001 to 2012				
Car dummy	0.48	0.00	0	1
mpg	22.01	21.45	13.32	112.23
Weight (1000lbs)	3.92	3.62	1.60	7.07
Vehicle horsepower	217	210	63	445
Registration	67548	37070	0	891482

Note: The number of observations is 7464, 8720, and 10334 for 2000, 2005, and 2008 vehicle population profile, respectively. The number of observations for new vehicles from 2001 to 2012 is 2411. The mean and standard deviations of vehicle age and attributes are weighted using the number of registrations. The oldest vintage in our data set is 1974. The vehicle with the highest mpg is a 2012 Mitsubishi I with a 126 and 99 for city and highway driving, respectively.

Table 2: Parameter Estimates in the VAR(1) Process

Variable	Eq1: Income Est. (1)	Eq1: Income S.E. (2)	Eq2: Gas price Est. (3)	Eq2: Gas price S.E. (4)
Constant	2.167	0.582	-0.749	1.244
Income	0.669	0.093	0.189	0.200
Gas price	-0.163	0.048	0.908	0.103

Error covariance	Income	Gas price
Income	0.0149	
Gas price	-0.0121	0.0684

Note: The estimation is based on detrended data of average household income and annual gasoline prices from 1967 to 2012. The variables are in 2008 dollars. The dependent variable in equation 1 (columns 1 and 2) is average household income and that in equation 2 (columns 3 and 4) is gasoline price.

Table 3: Vehicle Price Depreciation

Variables	Est.	S.E.
Age	0.379	0.066
Age*Car dummy	-0.002	0.005
Age*US Big Three dummy	0.018	0.008
Age*Japanese Three dummy	0.039	0.008
Age*European dummy	0.034	0.010
Age*Luxury dummy	0.021	0.008
log(MSRP)*age	-0.057	0.006
R^2	0.946	
No. of observations	7923	

Note: The dependent variable is log(used price/new price). The results are from OLS and the standard errors are clustered at the brand-type level (e.g., Ford cars, Ford trucks).

Table 4: Hedonic Price Regression

Variables	Est.	S.E.
Cars	-0.036	0.340
Weight	0.530	0.116
Weight^2	-0.042	0.011
Weight*car dummy	-0.038	0.188
Weight^2*car dummy	-0.005	0.025
Horsepower	0.368	0.108
Horsepower^2	-0.024	0.022
Horsepower*car dummy	0.121	0.129
Horsepower^2*car dummy	-0.006	0.025
Gallons per 100 miles (GPM)	-0.066	0.046
GPM^2	0.003	0.003
GPM*car dummy	-0.043	0.098
GPM^2*car dummy	0.015	0.009
R^2	0.929	
Number of Observations	7750	

Note: The data include new vehicle models sold from 2001 to 2012 and vehicle models appeared in the 2000 vehicle stock (most of vehicle models sold from 1974 to 2000). The dependent variable is log(new vehicle price). The results are from OLS and vintage fixed effects and make fixed effects are included in the regression. The standard errors are clustered at the brand-type level (e.g., Ford cars, Ford trucks).

Table 5: OLS Regressions of Scrappage Rate

Variable	Est.	S.E.	Est.	S.E.
Panel 1: five-year scrappage rate from 2001 to 2005				
Constant	0.101	0.017	0.059	0.020
Car dummy	-0.053	0.022	-0.065	0.021
Log(gpm)	-0.108	0.009	-0.139	0.009
Log(gpm) * car dummy	-0.110	0.013	-0.111	0.013
Log(age+1)	0.162	0.003	0.160	0.002
Log(age+1) * car dummy	0.092	0.004	0.101	0.003
Make fixed effects	No		Yes	
R^2	0.729		0.781	
Panel 2: three-year scrappage rate from 2006 to 2008				
Constant	-0.064	0.012	-0.049	0.014
Car dummy	-0.035	0.016	-0.045	0.016
Log(gpm)	-0.006	0.007	-0.033	0.007
Log(gpm) * car dummy	-0.083	0.010	-0.082	0.010
Log(age+1)	0.096	0.002	0.092	0.002
Log(age+1) * car dummy	0.080	0.003	0.086	0.003
Make fixed effects	No		Yes	
R^2	0.645		0.688	

Note: The dependent variable is the scrappage rate. The number of observations is 7464 in panel 1 and 8720 in panel 2. Log(gpm) is the logarithm of gallon per 100 miles.

Table 6: Parameters from the Structural Model

Variables	Specification 1		Specification 2		Specification 3	
	Est.	S.E.	Est.	S.E.	Est.	S.E.
User cost/household income	-6.103	1.006	-6.208	1.036	-21.068	2.628
Constant for cars	0.107	0.447	2.001	0.235	1.643	0.051
Log(age+1)	-1.010	0.085	-0.430	0.025	-1.206	0.050
Log(age+1)^2	-0.095	0.030	-0.138	0.017	-0.055	0.008
Log(horsepower)	0.195	0.053	0.185	0.081	0.161	0.112
Log(weight)	0.914	0.249	1.045	0.146	0.888	0.082
Constant for trucks	0.784	0.446	2.072	0.208	2.111	0.089
Transaction cost	1.018	0.476	1.158	0.455	0.833	0.165
Unobserved attributes	0.138	0.070			0.645	0.020
$\text{Unobserved attributes}^2$	0.325	0.189			0.319	0.144
Random Coefficients:						
Constant			0.576	0.148	0.274	0.059
Log(weight)			0.210	0.075	0.689	0.190

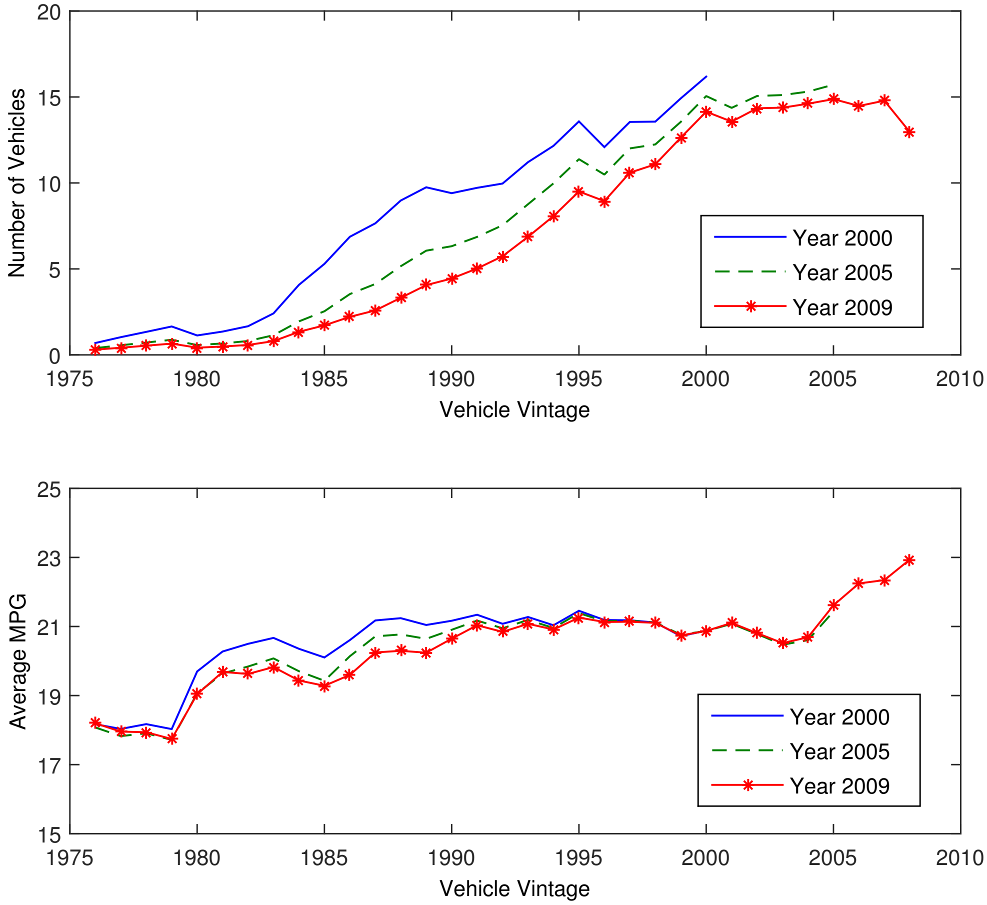
Note: The estimation results are from simulated GMM which are based on the assumption that prediction errors on new vehicle sales and used-vehicle stock are not correlated with observed vehicle attributes. The first specification has no random coefficients on consumer preference. The second specification adds random coefficients on consumer preference for owning a vehicle and for vehicle weight but drops the two variables for unobserved attributes. The user cost is defined as the annual rental price of the vehicle (price in the current period - discounted price in the next period) plus the fuel cost). The random coefficients are the standard deviations of normal distributions. The last specification includes both random coefficients and unobserved attributes. The results for specifications 2 and 3 are based on 100 randomized Halton draws, which produce similar results with 75 draws.

Table 7: Comparison of Alternative Policy Designs

Scenarios	Eligibility Requirement				Scrap	Enviro.	Eligible	Induced	Induced	Cost per	Cost per
	Trade-in		New: cars and trucks		value	benefit	sales	sales	spending	sales	$ spending
	Age	mpg	mpg/MSRP	Tiers	in Bil.$	in Bil.$	in Mil.	In Mil.	in Bil.$	in $1000	in $
1(baseline)	25	18	22 and 18	2	7.762	0.160	4.787	3.379	48.352	8.336	0.583
2	25	18	22 and 18	1	7.625	0.127	4.780	3.342	49.857	8.402	0.563
3	25	No	22 and 18	1	9.076	0.138	7.171	4.331	72.125	6.816	0.409
4	25	No	24 and 19	1	8.968	0.193	6.715	4.618	71.411	6.349	0.411
5	25	No	$27000	1	9.096	0.145	6.596	4.662	67.413	6.339	0.438
6	25	No	$22000	1	8.709	0.067	5.678	4.798	57.443	6.090	0.509
7	No	No	$22000	1	10.125	0.054	5.225	4.482	52.502	6.846	0.584
8	No	No	No	1	8.593	0.029	8.955	3.519	67.573	8.274	0.431
9(2007)	25	18	22 and 18	2	7.419	0.103	4.650	3.285	51.719	8.287	0.526

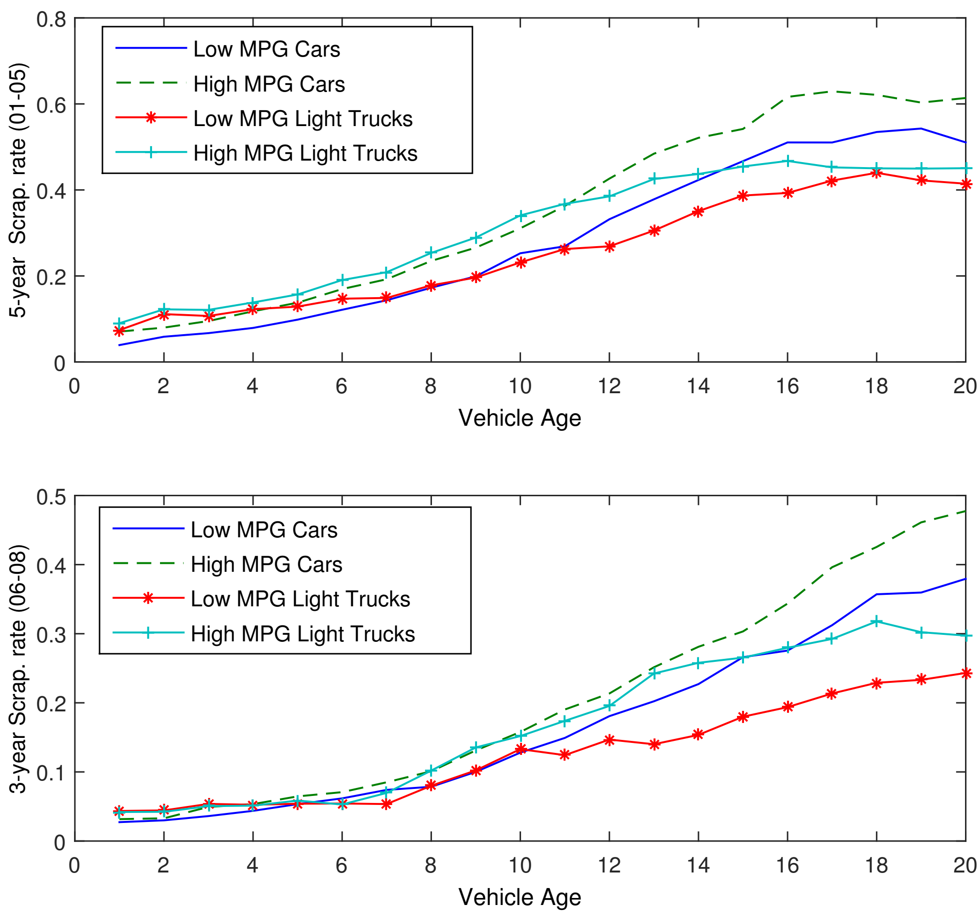
Note: The benchmark policy has the same key eligibility rules as in the real program but with a duration of one year and the total subsidy is $20.56 Billion. Under scenarios 2-8, the subsidy level is chosen so that the total subsidy would be the same as the benchmark policy. Scenario 9 has the same rules as the benchmark policy but is assumed to be implemented under the average income and gasoline price levels observed in 2007, resulting in the total subsidy of $19.90 Billion. The scrap value is the total lost value from the scrappage of the trade-in vehicles. The environmental benefits from the programs are avoided damages from reductions in carbon emissions and four criteria pollutants. Induced sales are the additional sales that would not have happened without the program and induced spending is the total consumer spending on these induced sales. The last two columns are the net cost (total subsidy + scrap value - environmental benefit) for each unit of induced vehicle sales and induced consumer spending on new vehicles. These two provide different cost-effectiveness measures. The dynamic impacts of scenarios 3 and 6 relative to the benchmark policy are plotted in Figure .

Figure 1: Vehicle Registration and Average mpg by Vintage



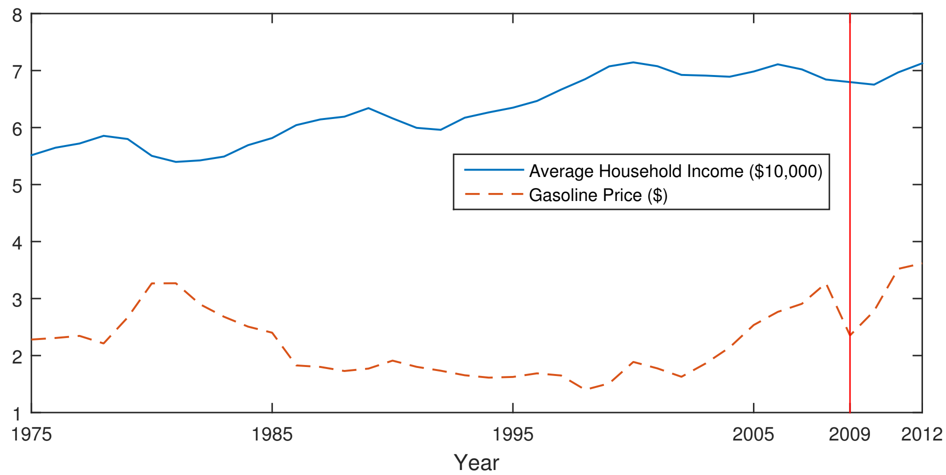
Note: The top graph shows the total number of passenger vehicles in the U.S. by vintage from 1976 in 2000, 2005, and 2008 from National Vehicle Population Profile. The bottom graph shows the average mpg of vehicles by vintage in 2000, 2005, and 2008.

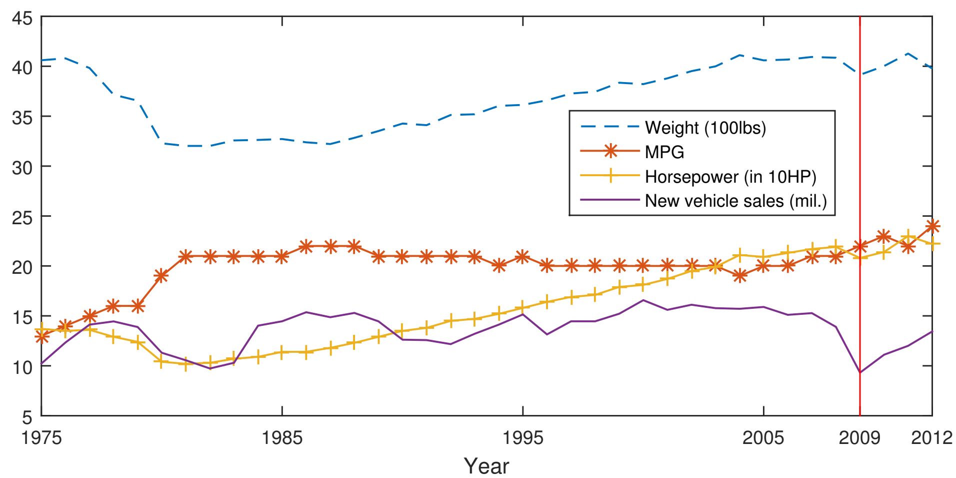
Figure 2: Scrappage Rate by Type and fuel economy during 2001-2005 and 2006-2008



Note: The top graph shows the 5-year scrappage rate from 2001 to 2005 for passenger cars and light trucks for two levels of fuel economy. Low mpg cars include passenger cars below the median level of vehicle mpg of all cars. Other categories are similarly defined. The bottom graph shows the 3-year scrappage rate from 2005 to 2008.

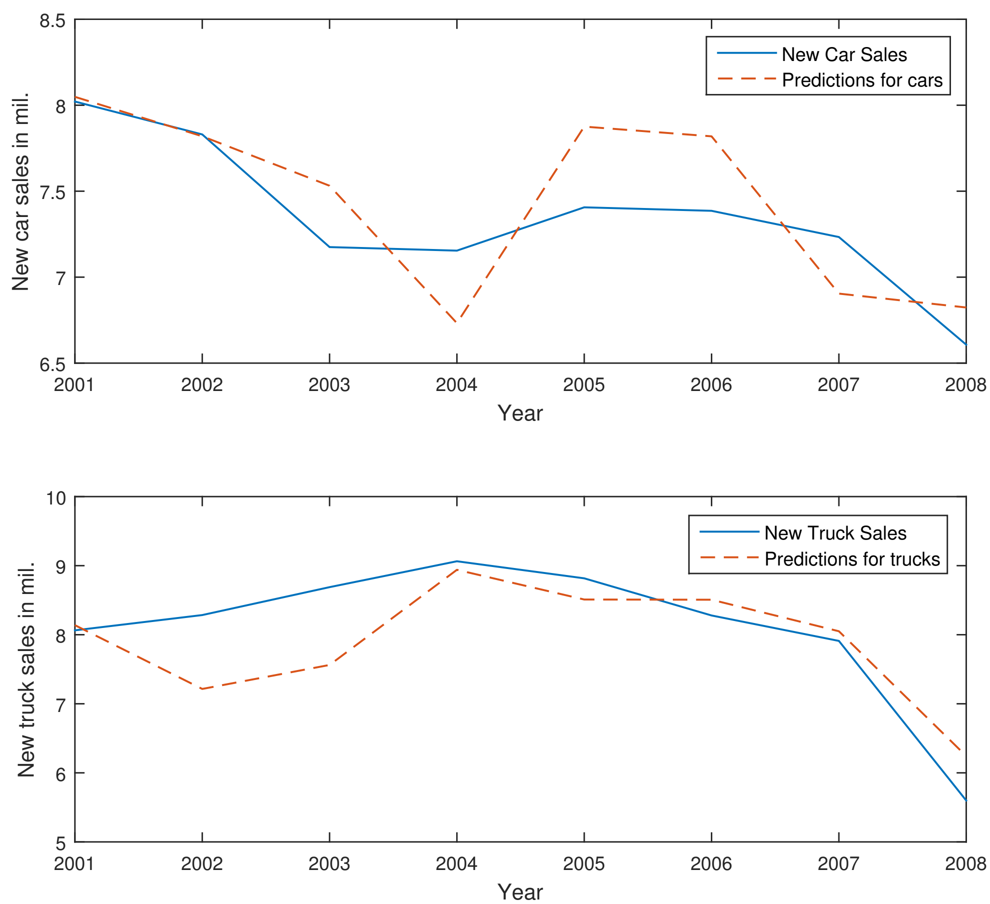
Figure 3: State Variables, New Vehicle Sales and Average mpg





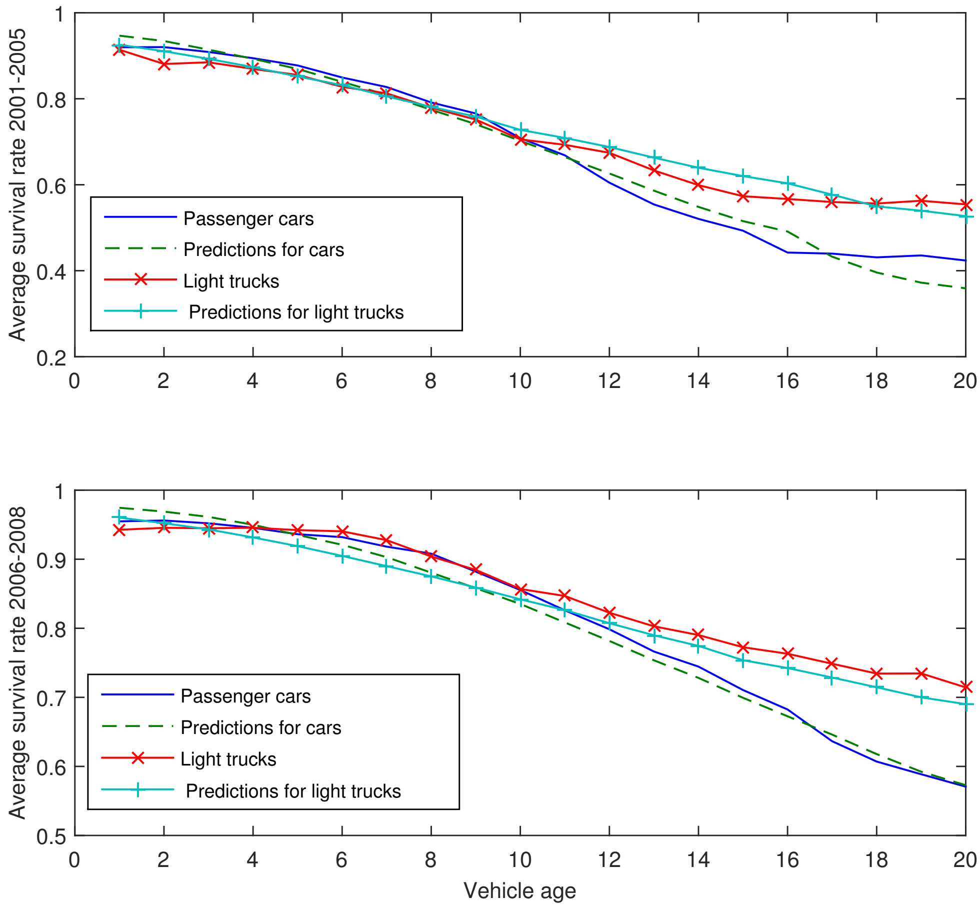
Note: The top graph shows average national household income, average vehicle price, and annual gasoline price in 2008 dollars. The bottom graph shows the total units of new vehicle sales and their average horsepower, weight and mpg.

Figure 4: Observed and Predicted New Vehicles Sales 2001 to 2008



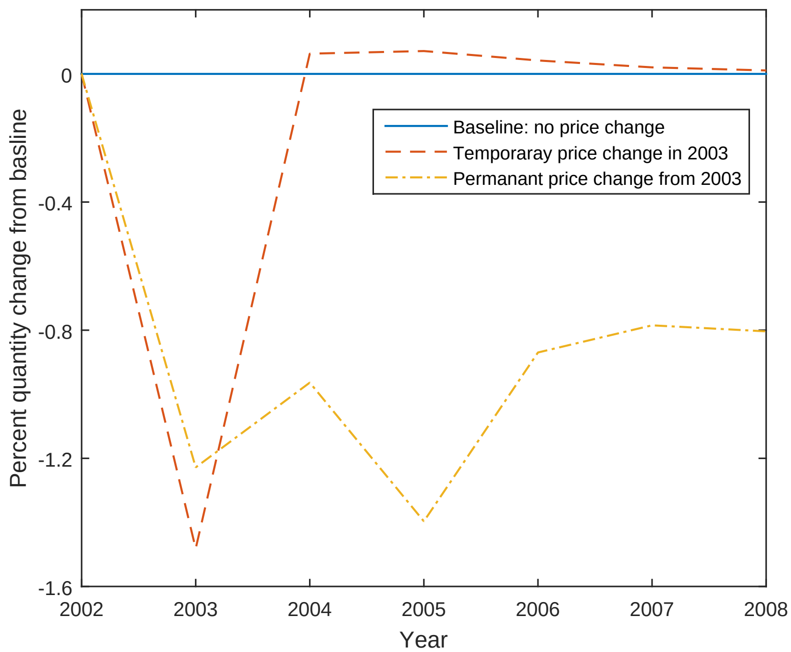
Note: The plots are based on the model estimates from specification 3 in Table 6. The top graph shows observed and predicted new sales for cars while the bottom graph for light trucks from 2001 to 2008.

Figure 5: Observed and Predicted Survival Rates by Age



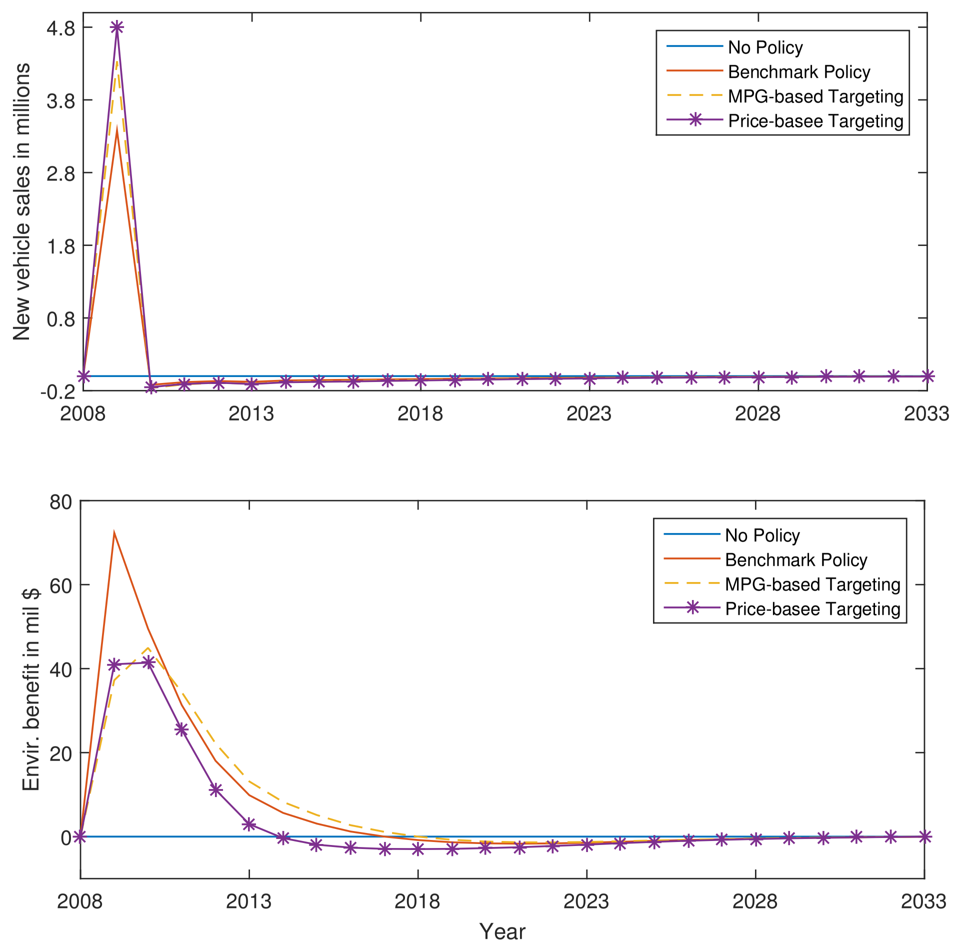
Note: The plots are based on the model estimates from specification 3 in Table 6. The top graph shows observed and predicted 5-year survival rates from 2001 to 2005 by vehicle type and age. The bottom graph shows observed and predicted 3-year survival rates from 2001 to 2005 by vehicle type and age.

Figure 6: Sales Impact from a Temporary and Permanent Price Change



Note: The plot is based on the model estimates from specification 3 in Table 6. It depicts the impacts on sales from a one-percent temporary and permanent price change from 2003. We assume that the stochastic processes governing the evolution of the log-inclusive value and the flow utility are not affected by the price increase in either scenarios. For temporary shocks, we assume that the logit-inclusive value in 2004 is based on the logit-inclusive value in 2003 under the scenario of no price increase. For permanent shocks, the logit-inclusive values in 2004 and forward are based on realized values in the previous period with the price increase.

Figure 7: Policy Comparisons in Sales and Environmental Outcomes



Note: The top graph shows the effects of a benchmark policy and two alternative polices on new vehicle sales, relative to the no-policy outcome. The Benchmark policy is a Cash for Clunkers program with the same rules as the real policy but with a duration of one year in 2009. The alternative policy with mpg-based targeting has requirement on the fuel economy of new vehicles with a minimal mpg of 22 for cars and 18 for light trucks. The alternative policy with price-based targeting has requirement on the MSRP of new vehicles with a maximum of $22000. These two alternative polices correspond to scenarios 3 and 6 in Table 7. The bottom graph shows the environmental benefits in dollar values from emission reductions.