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Shanjun Li
Cornell University

Chao Wei
George Washington University

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Institute for International Economic Policy
1957 E St. NW, Suite 502
Voice: (202) 994-5320
Fax: (202) 994-5477
Email: **iiep@gwu.edu**
Web: **www.gwu.edu/~iiep**

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

Shanjun Li † Chao Wei ‡

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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 based on several specifications all show that the design elements to achieve environmental benefits significantly limit the program impact on demand stimulus: the cost of vehicle demand stimulus after netting out environmental benefits can be up to 77 percent higher under the program than that from an alternative policy design without the design elements aimed at the environmental objective.

Keywords: Stimulus, Dynamic Discrete Choice Model, Vehicle Scrappage

JEL classification: E62, H23, H31, Q85

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†Assistant Professor, Dyson School of Applied Economics and Management, Cornell University, 405 Warren Hall, Ithaca, NY 14853. Email: SL2448@cornell.edu.

‡Associate Professor, Department of Economics, George Washington University, 2115 G Street, N.W., Washington DC 20052. Email: cdwei@gwu.edu.

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 larger 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 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 August 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 (International Institute of Labour Studies, 2011). The popularity of this type of green stimulus programs makes it an important target for our examination of the 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.

To quantify the tradeoff between the stimulus and environmental objectives, 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 uncertainties, each household decides whether to keep or scrap a vehicle, whether to purchase a new vehicle, and if so, what kinds of new vehicles to purchase. We estimate structural parameters of the model based on national vehicle stock data by vintage-nameplate in 2000, 2005, and 2008. With the estimated parameters, our model is capable of generating scrappage rates of vehicles by age, type and fuel economy under various aggregate economic conditions, and replicating stylized features which are broadly consistent with historical data such as procyclicality of new vehicle sales and the co-movement between gasoline prices and fuel economy of new vehicles.

Based on parameter 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. Our analysis based on various model specifications shows that these environmental elements could seriously reduce the amount of demand stimulus. After netting out the environmental benefits, a program with no explicit environmental elements would be much more cost-effective. Our findings, consistent with Tinbergen (1952), suggest that the environment objective is more effectively addressed by Pigouvian policies targeting vehicle emissions while the demand stimulus operates as a separate targeted program.[2]

[1] Although Alan Blinder is credited for popularizing the program, his proposal is quite different from how the real program was implemented. For example, his proposal does not contain requirement of new vehicle purchases after scrappage.

[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

We take a structural approach because not only are we interested in comparing the observed outcomes under the policy with the counterfactual outcomes of no policy for which a reduced-form analysis might be sufficient, but more importantly, we need to construct the outcomes under alternative policy designs. The CFC policy has multiple requirements and we are interested in alternative policy designs with some of the eligibility requirements modified. These alternative policies are not observed in the data and the outcomes cannot be constructed based on for example a control group without the policy. In addition, 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 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 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 builds upon and extends the literature on the dynamic vehicle ownership models, particularly those on the dynamic impact of vehicle scrappage programs. Adda and Cooper (2000, 2007) investigate fiscal impacts of provincial scrappage programs

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.

in France and Schiraldi (2011) studies vehicle scrappage subsidy programs in Italy, both in 1990's and without an explicit environmental objective. While Schiraldi (2011) offers a very rich dynamic model of vehicle demand, our analysis builds upon the model in Adda and Cooper (2000) for its parsimony, computational tractability and the aggregate nature of our data.[4] We extend Adda and Cooper (2000) in the following two critical dimensions. First, vehicles differ only by age in their model so the scrappage decisions on vehicles are no different from those on other durable goods. Our model incorporates additional vehicle characteristics such as fuel economy and vehicle type. This not only allows us to take advantage of rich data for better model fit, but also more importantly to evaluate both stimulus and environmental impacts of the program where the eligibility rules are specified over both age and fuel economy. Second, our model incorporates consumer heterogeneity in preferences for vehicle characteristics, which leads to more reasonable substitution patterns across different vehicle choices and more credible analysis into the tradeoff between the stimulus and environmental objectives.

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-specific attributes including type, age and fuel efficiency. Such an explicit reliance enriches the modeling of vehicle ownership decisions. Our paper is also related to Wei (2012), 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.

[4] Schiraldi (2011) estimates an ambitious dynamic demand model to study vehicle scrappage subsidy programs in 1997 and 1998 in Italy based on transaction data on individual cars from 1994 to 2004. The model takes into account product differentiation, unobserved product attributes and consumer heterogeneity. To achieve computation feasibility, he employs the Inclusive Value Sufficiency assumption that log inclusive values (i.e., ex ante discounted lifetime utility) are sufficient statistics for consumers dynamic optimization problems introduced by Gowrisankaran and Rysman (2012).

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 accounts 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. 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 trade-in and new vehicles. The trade-in vehicle must be drivable; have been continually insured and registered by the same owner for the past year; be less than 25 years old; and have a combined fuel economy of 18 miles per gallon (mpg) or less (waived for very large pickup trucks and cargo vans). These requirements are to ensure that the trade-in vehicles would be used without the program and that removing them would generate emissions reduction. In addition, new vehicles have to satisfy certain minimum fuel economy requirement in order to qualify for the program. The minimum mpg is 22 for passenger automobiles, 18 for category 1 trucks, and 15 for category 2 trucks.[5] The level of subsidy depends on the mpg improvement of the new vehicle over the trade-in vehicle. The mpg requirement is the most stringent for passenger cars, but laxer across all truck categories. For example, a new passenger car must be at least 4 mpg better than the trade-in vehicle in order to qualify for the $3,500 rebate, and an improvement by 10 mpg is needed for the $4,500 rebate. For a new vehicle in category 1, mpg are required to improve by 2 and 5 respectively to qualify for the two rebate levels. These mpg requirements are designed to achieve a larger environmental benefit. In the counterfactual simulations, we will examine how these design elements affect program effectiveness on vehicle sales.

2.2 Data

The main data source for our estimation is the National Vehicle Population Profile (NVPP) database in year 2000, 2005, and 2008. The database, proprietarily maintained by R.L. Polk & Company, 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) to generate cross-sectional distributions of vehicles by age and mpg in 2000, 2005 and 2008.[6]

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. Table 1 provides the summary statistics for each of the three cross-sections. The mean and standard deviation of vehicle age, car dummy and mpg 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

[5] Category 1 trucks are "non-passenger automobiles" including SUVs, medium-duty passenger vehicles, pickup trucks, minivans and cargo vans. Category 2 trucks are large vans or large pickup trucks whose wheelbase exceeds 115 inches for pickups and 124 for vans. The definitions of truck categories and additional eligibility rules can be found at www.cars.gov.

[6] 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 $= 1/(0.55/\text{city mpg} + 0.45/\text{highway mpg})$.

recent vintages last longer than earlier vintages due to improvement in vehicle technology. The average vehicle age increased from 8.9 to 10.0 from 1995 to 2010 according to Polk's analysis based on their vehicle population profile data. 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.[7] The average mpg stays relatively stable during this period with a slight increase from 2005 to 2008.

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.[8] For each vehicle type, the scrappage rates are shown for

[7]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.

[8]The five-year scrappage rate for a given vehicle model from 2001 to 2005 is defined as the difference in

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, 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: annual average household income from the US census, annual gasoline prices from the Department of Energy, and average vehicle prices from WARDS Automotive Yearbook, all from 1967 to 2008. The top graph in Figure 3 plots these three variables in 2008 dollars from 1975 to 2008. 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 and their average mpg, both collected from the US EPA Light-Duty Vehicle fuel economy Technology Annual Report 2010. New vehicle sales are highly pro-cyclical: the correlation coefficient between household income and new vehicle sales is 0.783 from 1967 to 2008. When the average household income declined during the economic recessions in the early 1980s, 1990, 2001 and 2007, new vehicle sales dropped as well. 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

the number of registrations in 2000 and 2005 divided by the number of registrations in 2000.

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.

3 The Model

In this section, we construct a dynamic discrete choice model which will be taken to the data in the next section. The model is able to characterize household purchase and scrappage decisions under various economic conditions. Our model is built upon Adda and Cooper (2000, 2007) and we extend their models in three important dimensions. First, we allow the option of not owning any vehicles. This is important in understanding changes in vehicle ownership and vehicle sales. Second, our model incorporates richer vehicle characteristics such as vehicle type and fuel economy while in their models vehicles differ only by age. This is necessary in order to examine the CFC program which uses age, fuel economy and vehicle type in eligibility rules. Third, we allow consumer heterogeneity in preference for vehicle characteristics which permits more reasonable substitution pattern across different vehicle choices. We maintain two simplifying assumptions in Adda and Cooper (2000) for computational tractability. First, each household can at most own one vehicle at each period. This amounts to that in multi-vehicle households, decisions over each of the vehicles are separate. Second, there is no second-hand market for vehicles and a household holds a vehicle until scrappage. These two assumptions preclude some potentially important decision margins and we will discuss their implications on model estimates and policy analysis after we present the results.

3.1 Household's Optimization Problem

Time is infinite and discrete. The maximum life span of vehicles is N periods. There are two types of households: vehicle owners and non-owners. Both types of households, given a set of state variables, maximize their lifetime utility by making vehicle ownership decisions.

3.1.1 State Variables

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 three state variables: the average household income Y_t, the real gasoline price O_t, and the aggregate (real) price of new vehicles P_t. We use $\mathbf{S}_t \equiv \{Y_t, O_t, P_t\}$ to denote the vector of aggregate state variables.

We classify households as vehicle owners or non-owners based upon whether they enter a particular period with a vehicle or not. A household which owns a vehicle at the beginning of the period is characterized by a vector of household-specific state variables, denoted by $\mathbf{s}_t = \{\iota, a, \mathbf{\Omega_i}\}$, where ι characterizes the household's type in terms of its preference for gallons per mile (gpm, the inverse of mpg). We assume that ι can only take on two values from the set $\{0, 1\}$, corresponding to the low type and the high type. A household's type does not change over time and is unobservable to researchers. For a vehicle owner, a denotes the age of the vehicle at period t, and $\mathbf{\Omega_i}$ represents vehicle characteristics in terms of the ith combination of type and fuel economy (gpm) of the vehicle currently owned, where $i \in \mathcal{J} = \{1, 2, ...J\}$. Here $\mathcal{J}$ denote the set of new vehicle models available. For the sake of simplicity, we use $i = 0$ to denote the choice of not-owning a vehicle, and $\mathbf{\Omega}_0$ to denote the case when the household does not own any vehicles in that period. For a household that does not own a vehicle at the beginning of the period, the household-specific state variables are $\mathbf{s}_t = \{\iota, \mathbf{\Omega}_0\}$.

In addition to the household-specific state variables above, each household also privately observes a vector of choice-specific idiosyncratic taste shocks $\epsilon_{\mathbf{t}}$. For a vehicle owner, $\epsilon_{\mathbf{t}} = (\epsilon_t^k, \epsilon_{0t}, \epsilon_{1t}, ...\epsilon_{Jt})$, where ϵ_t^k corresponds to the option of keeping the vehicle, ϵ_{0t} corresponds to the option of scrapping without new purchase, and ϵ_{jt} corresponds to the jth option from $\mathcal{J}$. For a non-owner, $\epsilon_t = (\epsilon_t^n, \epsilon_{1t}, ...\epsilon_{Jt})$, where ϵ_t^n corresponds to the option of keeping the status quo. These shocks, unobservable to researchers, follow an identical and independent type-I extreme value distribution across time and households.

Two features of the model are worth discussing here. First, the usage of vehicle type and fuel economy to characterize a vehicle is admittedly simple. We believe that this simplification is likely to have small impacts on our policy analysis if any. As shown below, fuel economy affects consumer choices through: (1) its role as a catch-all vehicle attributes, i.e., to represent vehicle attributes such as horsepower and weight which tend to be highly correlated with fuel economy; and (2) its effect on fuel costs and consumption of numeraire goods. These two channels are separately defined and identified. It is reasonable to argue that consumers do not derive utility from fuel economy directly as they do from other attributes such as horsepower or weight. Fuel economy itself matters to consumers only due to the fact that it affects the cost of driving. That is, the second channel captures the real impact of fuel economy itself on consume choices and our policy analysis relies only on the second channel. This modeling choice follows Gramlich (2009) and is driven by the computational concern: the computational tractability is high on our priority list as it allows us to experiment with different model specifications.

Second, our model has a simple supply side: although prices of new vehicles change over time, we abstract away from supply side dynamics such as changes in vehicle attributes and product lines. We assume the choice set of new models to be the same across time for two reasons. First, the automobile industry is a multi-product oligopoly. Accounting for the dynamics on both demand and supply sides properly will come at the expense of computational tractability. Second, we believe that abstracting from the supply side dynamics will likely to be of little importance for the short-term policy we are interested in. The bill for the CFC program was first introduced in the Congress in March 2009 and passed in June 2009. The program lasted for only a month from late July to late August of 2009, covering about 0.68 million units of new vehicle sales relative to the annual sales of 10.4 million new vehicles. Given these features, the program is unlikely to have large impacts on the supply side (such as product choice and pricing decisions). The program mainly reduced the large inventory of dealerships during the program period and there was nearly perfect pass-through of the subsidy to consumers (Puller and West 2014).

3.1.2 Choice Set of Households

The decisions are made at the beginning of each period. A vehicle owner can choose to: (1) keep the vehicle, (2) scrap the vehicle and buy a new vehicle with certain characteristics; or (3) scrap the vehicle and become a non-owner. A non-owner can choose to: (1) remain a non-owner, or (2) buy a new vehicle with particular characteristics. We describe household decisions using vector $\psi = \{k, j^*\} \in \ominus$. Here k takes on two values. When $k = 1$, either the vehicle-owner or non-owner decides to keep the status quo. When $k = 0$, the vehicle owner decides not to keep the current vehicle, while the non-owner decides to purchase a new one. When $k = 0$, the variable $j^* \in \mathcal{J} \cup \{0\}$ denotes the optimal choice from the set of the new vehicle model plus the choice of not owning any vehicle. We assume that households can enjoy services of new 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.

Specifically, for a household that owns a vehicle characterized by its age (a) and other characteristics ($\mathbf{\Omega_i}$) at the beginning of period t (vehicle owner), the contemporaneous utility function is given by

$$u^o(\mathbf{s}_t, \mathbf{S}_t, \epsilon_t; \psi_t) = \begin{cases} \overline{u}^o\left(\iota, a, \mathbf{\Omega_i}, c_t^{o,i,i}\right) + \epsilon_t^k & \text{if } k_t = 1 \\ \overline{u}^o\left(\iota, 1, \mathbf{\Omega_j}, c_t^{o,i,j}\right) + \epsilon_{jt} & \text{if } k_t = 0, j^* = j \\ \overline{u}^n\left(c_t^{o,i,0}\right) + \epsilon_{0t} & \text{if } k_t = 0, j^* = 0. \end{cases} \tag{1}$$

The function $\overline{u}^o(\iota, a, \mathbf{\Omega_i}, c)$ represents the single-period deterministic utility from non-durable consumption c and service flow from owning a vehicle characterized by $\{a, \mathbf{\Omega_i}\}$. The function $\overline{u}^n\left(c_t^{o,i,0}\right)$ represents the single-period deterministic utility accrued to the household who decides to scrap the old vehicle and not purchase a new vehicle. $\epsilon_{\mathbf{t}}$, as discussed above, is the choice-specific idiosyncratic taste shock that is known to the household before its decision but unobserved to researchers.

We assume that $\overline{u}^o(\iota, a, \mathbf{\Omega_i}, c)$ is additively separable in nondurable goods consumption c and the service flow from vehicles. The service flow from a vehicle depends upon its age a and its characteristics, $\mathbf{\Omega_i}$, which represents a particular cross product of type and fuel economy $\{g, x\}$ with $i \in \mathcal{J}$. We assume that the type of vehicles, g, is chosen out of a bivariate index set of $\{1, 2\}$, where the index 1 denotes car and 2 denotes truck. We denote x as the fuel economy of vehicles and measure it in terms of gallons per miles. Specifically, the deterministic utility $\overline{u}^o(\iota, a, \mathbf{\Omega_i}, c_t)$ is given by

$$\begin{aligned} \overline{u}^o(\iota, a, \mathbf{\Omega_i}, c_t; \psi_t) \quad = \quad & \phi_{0,g} + \phi_{1,g}\log(a+1) + \phi_{2,g}\left[\log(a+1)\right]^2 \\ & + \phi_{3,g}(\iota)\log(x) + \mathbb{1}(k_t = 1)\alpha_k + \xi\frac{c_t(\psi_t)^{1-\gamma}}{1-\gamma}. \end{aligned} \tag{2}$$

We assume that the deterministic utility without owning a vehicle $\overline{u}^n(c_t; \psi_t)$ takes the following form:

$$\overline{u}^n(c_t; \psi_t) = \mathbb{1}(k_t = 1)\alpha_k + \xi\frac{c_t(\psi_t)^{1-\gamma}}{1-\gamma}. \tag{3}$$

The specification allows vehicle type-specific preference parameters. The first term, $\phi_{0,g}$, represents the household's utility from auto service per se, regardless of its age or fuel economy. The parameters $\phi_{1,g}$ and $\phi_{2,g}$ govern the dependence of utility upon the vehicle age. The parameter $\phi_{3,g}$, which governs the dependence of utility on fuel economy, is a function of the household's type to be specified below in equation (8). As we discussed above, the utility from fuel economy is used to capture the utility from other vehicle attributes such as horsepower and weight. The impact of fuel economy itself on consume choices is through fuel cost and numeraire good consumption c discussed below. The dependence of utility on age and fuel economy also differs across vehicle types. $\mathbb{1}(.)$ is an indicator function that takes value one when a household chooses to keep the status quo (i.e., $k_t = 1$). α_k captures the utility gain from keeping the status quo by a vehicle owner or non-owner. The taste parameter, ξ, affects the intratemporal marginal rate of substitution between auto services and nondurable consumption. The parameter γ affects the curvature of the utility function in nondurable consumption. We discuss how household decisions relate to ξ and γ in detail in Section 3.2.4. We note in passing that ξ and γ play different and related roles in the utility function. The identification of these two parameters, relying on the function form following the literature such as Adda and Cooper (2000), comes from cross-sectional and temporal variations in both vehicle scrappage and new vehicle purchases in our data.

Nondurable consumption c is equal to the household income minus expenditure, which include fuel expenditure on driving the vehicle with given characteristics and payment for a new vehicle in case of vehicle purchase plus the scrap value in case of scrappage. For a vehicle owner, the amount of nondurable consumption is a function of the household's decision ψ_t and aggregate and household-specific state variables:

$$c_t = \begin{cases} c_t^{o,i,i} = Y_t - F\left(a, g, x, O_t\right) - P^{(a)}_{g',x',t}, & \text{if } k_t = 1 \\ c_t^{o,i,j} = Y_t - P^{(1)}_{g',x',t} - F\left(1, g', x', O_t\right) + \pi\left(a, x, x', g, g'\right), & \text{if } k_t = 0, j_t^* = \{g', x'\} \\ c_t^{o,i,0} = Y_t + \overline{\pi}, & \text{if } k_t = 0, j_t^* = 0. \end{cases}$$

$F\left(a, g, x, O_t\right)$, to be specified in the next section, represents the fuel expenditure from driving the vehicle with attributes $\{a, g, x\}$ when the gasoline price is at O_t. We allow borrowing by assuming that all consumers take a five-year equal-installment auto loan with a fixed interest rate of three percent. Here $P^{(a)}_{g',x',t}$ represents the $a-$th period payment of a new vehicle with characteristics $\{g', x'\}$, whose full price would be $P_{g',x',t}$. The installment equals zero after the fourth year of purchase. In the special case when auto loan is not allowed, $P^{(1)}_{g',x',t}$ is equal to the full price of the vehicle, $P_{g',x',t}$, while $P^{(a)}_{g',x',t}$ equals 0 for $a > 1$.

$\pi(a, x, x', g, g')$ represents the scrap value of the vehicle. Under the CFC program, it depends upon the age, type, and fuel economy of the new and replaced vehicles. Without the program, we assume the scrap value to be \$500 in our baseline models and conduct robustness checks with it being zero.[9]

The contemporary utility of a household which starts the period as a non-owner also depends upon the decision ψ_t. Specifically

$$u^n(s_t, S_t, \epsilon_t; \psi_t) = \begin{cases} \overline{u}^n\left(c_t^{n,0,0}\right) + \epsilon_t^k & \text{if } k_t = 1 \\ \overline{u}^o\left(\iota, 1, \mathbf{\Omega_j}, c_t^{n,0,j}\right) + \epsilon_{jt} & \text{if } k_t = 0, j^* = j, \end{cases} \tag{4}$$

where the deterministic utility are defined as in equations (2) and (3). The nondurable consumption for a non-owner is given by,

$$c_t = \begin{cases} c_t^{n,o,o} = Y_t, & \text{if } k_t = 1 \\ c_t^{n,0,j} = Y_t - P^{(1)}_{g',x',t} - F(1, g', x', O_t), & \text{if } k_t = 0, j_t^* = \{g', x'\}. \end{cases}$$

3.1.4 Value Functions of Vehicle Owners and Non-owners

Given the aggregate and household-specific state variables, households make vehicle ownership decisions at the beginning of each period to maximize their lifetime utility. The maximization problem can be formulated into two value functions, one for vehicle owners and the other for non-owners.

Let $V(\iota, a, \mathbf{\Omega}_i, \mathbf{S}, \epsilon)$ represents the value function of a representative household of type ι, with current income Y, owning a vehicle with the characteristics $\{a, \mathbf{\Omega}_i\}$, and observing private taste shocks ϵ. Given the aggregate and individual state variables, the household decides whether to keep the currently-owned vehicle, scrap the vehicle and replace it with a new one, or just scrap the vehicle but not replace it.

Following the literature, we make the conditional independence assumption: conditional on the decision (ψ) and the observable state variables ($\mathbf{s}$ and $\mathbf{S}$) in the current period, the observable state variables in the next period ($\mathbf{s}'$ and $\mathbf{S}'$) do not depend on current

[9] The scrappage value for most vehicles can vary between zero and \$1000. In case of vehicle donation for a tax reduction, it will depend on the marginal tax bracket of the household and the appraisal value of the vehicle.

idiosyncratic shocks (ϵ). The value function of vehicle owners, $V(\iota,a,\mathbf{\Omega}_i,\mathbf{S},\epsilon)$, is given by,

$$V(\iota,a,\mathbf{\Omega}_i,\mathbf{S},\epsilon)=\max_{\psi\in\Psi}\left\{\begin{array}{c}\overline{u}^o(\iota,a,\mathbf{\Omega_i},c^{o,i,i})+\epsilon^k+\beta\mathbb{E}V(\iota,a+1,\mathbf{\Omega}_i,\mathbf{S}',\epsilon'|\mathbf{s},\mathbf{S})\\ \max\limits_{1\le j\le J}\left\{\overline{u}^o(\iota,1,\mathbf{\Omega}_j,c^{o,i,j})+\epsilon_j+\beta\mathbb{E}V(\iota,2,\mathbf{\Omega}_j,\mathbf{S}',\epsilon'|\mathbf{s},\mathbf{S})\right\}\\ \overline{u}^n(c^{o,i,0})+\epsilon_0+\beta\mathbb{E}V^n(\iota,\mathbf{S}',\epsilon'|\mathbf{s},\mathbf{S})\end{array}\right\}.$$

$V^n(\iota,\mathbf{S},\epsilon)$ represent the value function of a representative household which does not own any vehicle. Given the aggregate and household-specific state variables, the household decides whether to keep its status quo, or purchase a new vehicle characterized by $\mathbf{\Omega}_j$. The value function for non-owners, $V^n(\iota,\mathbf{S},\epsilon)$, is given by,

$$V^n(\iota,\mathbf{S},\epsilon)=\max_{\psi\in\Psi}\left\{\begin{array}{c}\max\limits_{1\le j\le J}\left\{\overline{u}^o(\iota,1,\mathbf{\Omega}_j,c^{n,0,j})+\epsilon_j+\beta\mathbb{E}V(\iota,2,\mathbf{\Omega}_j,\mathbf{S}',\epsilon'|\mathbf{s},\mathbf{S})\right\}\\ \overline{u}^n(c^{n,0,0})+\epsilon^n+\beta\mathbb{E}V^n(\iota,\mathbf{S}',\epsilon'|\mathbf{s},\mathbf{S})\end{array}\right\}.$$

Because ϵ 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 is revealed:

$$\begin{aligned}\overline{V}(\iota,a,\mathbf{\Omega}_i,\mathbf{S}) &= \int V(\iota,a,\mathbf{\Omega}_i,\mathbf{S},\epsilon)\,dF(\epsilon),\\ \overline{V}^n(\iota,\mathbf{S}) &= \int V^n(\iota,\mathbf{S},\epsilon)\,dF(\epsilon).\end{aligned}$$

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:

$$\overline{V}(\iota,a,\mathbf{\Omega}_i,\mathbf{S})=\int\max_{\psi\in\Psi}\left\{\begin{array}{c}\overline{u}^o(\iota,a,\mathbf{\Omega_i},c^{o,i,i})+\epsilon^k+\beta\mathbb{E}\overline{V}(\iota,a+1,\mathbf{\Omega}_i,\mathbf{S}'|\mathbf{s},\mathbf{S})\\ \max\limits_{1\le j\le J}\left\{\overline{u}^o(\iota,1,\mathbf{\Omega}_j,c^{o,i,j})+\epsilon_j+\beta\mathbb{E}\overline{V}(\iota,2,\mathbf{\Omega}_j,\mathbf{S}'|\mathbf{s},\mathbf{S})\right\}\\ \overline{u}^n(c^{o,i,0})+\epsilon_0+\beta\mathbb{E}\overline{V}^n(\iota,\mathbf{S}'|\mathbf{s},\mathbf{S})\end{array}\right\}dF(\epsilon).$$

$$\overline{V}^n(\iota,\mathbf{S})=\int\max_{\psi\in\Psi}\left\{\begin{array}{c}\max\limits_{1\le j\le J}\left\{\overline{u}^o(\iota,1,\mathbf{\Omega}_j,c^{n,0,j})+\epsilon_j+\beta\mathbb{E}\overline{V}(\iota,2,\mathbf{\Omega}_j,\mathbf{S}'|\mathbf{s},\mathbf{S})\right\}\\ \overline{u}^n(c^{n,0,0})+\epsilon^n+\beta\mathbb{E}\overline{V}^n(\iota,\mathbf{S}'|\mathbf{s},\mathbf{S})\end{array}\right\}dF(\epsilon).$$

3.2 Household's Optimization Decisions

In this section, we describe the household's optimal decisions on whether to scrap a vehicle, whether to purchase a new vehicle, and if purchasing a new vehicle, what type and fuel economy of new vehicles to choose. We then proceed to examine the impact of aggregate state variables and scrappage subsidies on optimal decision making.

3.2.1 Vehicle-Owners' Scrappage and Purchase Decisions

The decision on scrapping the vehicle is essentially an optimal stopping problem. The household decides whether to 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 a household of type ι, the aggregate probability of keeping a vehicle with characteristics $\{a, \mathbf{\Omega}_i\}$ in the state $\{\mathbf{s}, \mathbf{S}\}$ is given by a logistic function:

$$\mu_{ii}^{k}\left(\iota, a, \mathbf{\Omega}_i, \mathbf{S}\right) = \frac{\exp\left[\nu_{ii}^{k}\left(\iota, a, \mathbf{\Omega}_i, \mathbf{S}\right)\right]}{\exp\left[\nu_{ii}^{k}\left(\iota, a, \mathbf{\Omega}_i, \mathbf{S}\right)\right] + \sum_{h=0}^{J} \exp\left[\nu_{ih}^{r}\left(\iota, a, \mathbf{\Omega}_i, \mathbf{S}\right)\right]}, \tag{5}$$

where

$$\begin{aligned}
\nu_{ii}^{k}\left(\iota, a, \mathbf{\Omega}_i, \mathbf{S}\right) &= \overline{u}^{o}\left(\iota, a, \mathbf{\Omega_i}, c^{o,i,i}\right) + \beta\mathbb{E}\overline{V}\left(\iota, a+1, \mathbf{\Omega}_i, \mathbf{S}'|\mathbf{s}, \mathbf{S}\right); \\
\nu_{ij}^{r}\left(\iota, a, \mathbf{\Omega}_i, \mathbf{S}\right) &= \begin{cases} \overline{u}^{o}\left(\iota, 1, \mathbf{\Omega}_j, c^{o,i,j}\right) + \beta\mathbb{E}\overline{V}\left(\iota, 2, \mathbf{\Omega}_j, \mathbf{S}'|\mathbf{s}, \mathbf{S},\right) & j \geq 1 \\ \overline{u}^{n}\left(c^{o,i,0}\right) + \beta\mathbb{E}\overline{V}^{n}\left(\iota, \mathbf{S}'|\mathbf{s}, \mathbf{S},\right) & j = 0. \end{cases}
\end{aligned}$$

The scrappage rate among vehicles of age a and characteristics $\mathbf{\Omega}_i$ is $1 - \mu_{ii}^{k}\left(\iota, a, \mathbf{\Omega}_i, \mathbf{S}\right)$. As shown in the above equation, a higher status-quo parameter α_k raise the probability of keeping vehicles across all ages. The scrappage rate depends upon both aggregate state variables and the characteristics of the vehicle under consideration.

Once the scrappage decision is made, the household needs to make optimal decisions on whether to purchase a new vehicle and what type and fuel economy of new vehicles to be purchased. Vehicle characteristics affect the price of a new vehicle, the utility from auto service and total cost of driving over the vehicle's lifetime. The household's decision on vehicle characteristics reflects the tradeoff between current purchase price and the future flow of cost and utility.

For the same vehicle-owner household, the aggregate probability of making the decision $\psi = \{k = 0, j\}$, where $j \in \mathcal{J} \cup \{0\}$, is given by

$$\mu_{ij}^{r}\left(\iota, a, \mathbf{\Omega}_i, \mathbf{S}\right) = \frac{\exp\left[\nu_{ij}^{r}\left(\iota, a, \mathbf{\Omega}_i, \mathbf{S}\right)\right]}{\exp\left[\nu_{ii}^{k}\left(\iota, a, \mathbf{\Omega}_i, \mathbf{S}\right)\right] + \sum_{h=0}^{J} \exp\left[\nu_{ih}^{r}\left(\iota, a, \mathbf{\Omega}_i, \mathbf{S}\right)\right]}, \tag{6}$$

Here $\mu_{ij}^{r}\left(\iota, y, a, \mathbf{\Omega}_i, \mathbf{S}\right)$ represents the probability of the given household purchasing a new vehicle endowed with $\mathbf{\Omega}_j$ when $j > 0$. When $j = 0$, it represents the probability of the given household making the decision of scrapping its vehicle and not buying a new one.

3.2.2 Non-Owners' Purchase Decisions

For a household that does not own any vehicles to start with, the aggregate probabilities of its decisions are given by

$$\mu_{0j}^{n}\left(\iota, \mathbf{S}\right) = \frac{\exp\left[\nu_{0j}^{n}\left(\iota, \mathbf{S}\right)\right]}{\sum_{h=0}^{J} \exp\left[\nu_{0h}^{n}\left(\iota, \mathbf{S}\right)\right],} \tag{7}$$

where

$$\begin{aligned} \nu_{00}^{n}\left(\iota, \mathbf{S}\right) &= \overline{u}^{n}\left(c^{n,0,0}\right) + \beta \mathbb{E} \overline{V}^{n}\left(\iota, \mathbf{S}' | \mathbf{s}, \mathbf{S},\right) \\ \nu_{0j}^{n}\left(\iota, \mathbf{S}\right) &= \overline{u}^{o}\left(\iota, 1, \mathbf{\Omega}_j, c^{n,0,j}\right) + \beta \mathbb{E} \overline{V}\left(\iota, 2, \mathbf{\Omega}_j, \mathbf{z}', \mathbf{S}' | \mathbf{s}, \mathbf{S},\right). \end{aligned}$$

Given the above expressions, the probability of a non-vehicle owner keeping the status quo is $\mu_{00}^{n}\left(\iota, \mathbf{S}\right)$, while the probability of such a household purchasing a vehicle endowed with $\mathbf{\Omega}_j$ is given by $\mu_{0j}^{n}\left(\iota, \mathbf{S}\right)$.

3.2.3 Impacts of Aggregate State Variables

The aggregate state variables, $\{Y_t, O_t, P_t\}$, play important roles in the household's decisions. An increase in current aggregate income, Y_t, relaxes the household's budget constraint for now and alters the marginal utility of current nondurable consumption relative to that of future periods. As a result, an increase in current aggregate income is likely to encourage vehicle scrappage and new vehicle sales. An increase in the volatility of aggregate income, however, may delay the decision to scrap vehicles, due to the irreversible nature of such decisions.

An increase in gasoline prices, O_t, raises the fuel cost of driving all vehicles. The increase in driving costs affects both vehicle scrappage and purchase 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 scrap the vehicle for a different model. Higher gasoline prices may provide incentives to scrap those aged and fuel-inefficient vehicles and purchase more fuel efficient new vehicles. On the other hand, higher gasoline prices tighten the household's budget constraint, and consequently may delay its scrappage and purchase decisions. An increase in the volatility of gasoline prices may create the option to wait to make decisions on appropriate vehicles to purchase. Such an option is likely to delay vehicle purchase decisions and reduce new vehicle sales. An increase in the average vehicle prices, P_t, is likely to discourage scrappage and reduce new vehicle sales.

Given the dynamic nature of the model, decisions on vehicle scrappage, purchase and characteristics are interrelated and jointly determined. The optimal scrappage rate depends upon the characteristics of a particular vehicle, while the decision on whether to purchase a vehicle and the characteristics of the new vehicle also depend upon the vehicle's life span, as indicated by its scrappage rate.

3.2.4 Effects of Scrappage Subsidies on Decision Making

In the model, we assume that a household is eligible for scrappage subsidies which may depend upon the age of the scrapped vehicle, and the differences in the fuel economy between the new and scrapped 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 larger amount of scrappage subsidies relaxes the household's budget constraint. This increases the relative value of scrapping the vehicle, and reduces the marginal cost of purchasing a new vehicle. The extent of substitution, however, depends crucially upon γ and ξ, the two preference parameters in the contemporary utility function. The parameter γ captures both the curvature of the utility function and the intertemporal elasticity of substitution in our expected utility framework. When γ is high, households are less willing to substitute consumption of nondurables across time. When γ is zero, the utility becomes linear in nondurable consumption, and the elasticity of substitution becomes infinite.

The parameter ξ is a conversion factor which makes utility from nondurables comparable with that from the service flow of vehicles. The purchase of a new vehicle is equivalent to giving up part of current and future stream of nondurable consumption in exchange for utility gained from utilizing a vehicle before it being scrapped. The sacrifices in the current and future nondurable consumption are respectively due to the up-front cost of vehicle purchase and subsequent gasoline expenditure. A higher ξ implies that nondurable goods are relatively more valuable than the utility stream from durable goods in the future, thus likely dampening the incentives for vehicle purchase.

We now turn to the substitution across choices in terms of type and fuel economy. When deciding on the optimal fuel economy of new vehicles, the household is balancing the marginal utility gain of driving a vehicle with a certain fuel economy against the marginal cost of purchasing the vehicle of the specific fuel economy and paying for fuel costs. 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 marginal cost of purchasing vehicles of higher fuel economy decreases as well. The extent of substitution across vehicles of different fuel economy, however, depends crucially upon $\phi_{3,g}(\iota)$, which captures the household's taste toward a particular fuel economy. If a household is strongly averse to fuel efficient vehicles (e.g., due to strong preference for horsepower and size), 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.

3.3 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, characteristics (age, type and fuel economy), heterogeneous tastes and income across households, our model can generate aggregate sales of new vehicles and the distribution of vehicles across age, type and fuel economy over time based on households' optimal scrappage and purchase decisions. The evolution of vehicle ownership distribution is then used in the estimation and counterfactual simulations as well.

We define $G_0(a, \Omega_i)$ as the observed distribution of vehicles by vehicle age and characteristics (type and fuel economy defined by gpm) in the initial year t_0. We further define $\widehat{G}_0(\iota, a, \Omega_i)$ as the cross-sectional distribution of households' heterogeneous tastes, vehicle age and characteristics prior to their scrappage and purchase decisions in year t_0. To construct the initial distribution of consumer types, we assume that all non-vehicle owners in year t_0 is of low type ($\iota = 0$).[10] The probability of being low-type ($\iota = 0$) among those who own vehicles with characteristics Ω_i in year t_0 is a logistic function of vehicle fuel efficiency (x_i):

$$Pr_0(\iota = 0|\Omega_i) = \frac{\exp(\chi_0 + \chi_1 log(x_i))}{1 + \exp(\chi_0 + \chi_1 log(x_i))}. \tag{8}$$

The type distribution conditional on vehicle ownership can be updated over time based on the initial distribution and household decisions.

Accordingly we can write $\widehat{G}_0(\iota, a, \Omega_i)$ as

$$\widehat{G}_0(\iota, a, \Omega_i) = G_0(a, \Omega_i) Pr_0(\iota|\Omega_i). \tag{9}$$

Given the cross-sectional distribution $\widehat{G}_0(\iota, a, \Omega_i)$, our model implies the following evolution of distribution over time:

$$\widehat{G}_{t+1}(\iota, a+1, \Omega_i) = \mu_{ii}^k(\iota, a, \mathbf{\Omega}_i, \mathbf{S}_t) \widehat{G}_t(\iota, a, \Omega_i), \ t \geq 0. \tag{10}$$

The number of vehicles characterized by $\{a+1, \Omega_i\}$ and owned by households of type ι in year $t+1$ is equal to the number of vehicles that are one year younger in the previous period, with the same characteristics, and carried over (not scrapped) by the households of type ι.

The distribution of new vehicles evolves as follows,

$$\begin{aligned} \widehat{G}_{t+1}(\iota, 1, \Omega_j) \quad = \quad & \sum_{i=1}^{J} \sum_{a \geq 1} \left[\mu_{ij}^r(\iota, a, \mathbf{\Omega}_i, \mathbf{S}_t) \widehat{G}_t(\iota, a, \Omega_i) \right] \\ & + \mu_{0j}^n(\iota, \mathbf{S}_t) n_t(\iota), \end{aligned} \tag{11}$$

[10] This restriction is made based on results from initial estimations with more flexible specifications on the distribution. We cannot precisely estimate the type distribution among non-owners in those specifications, likely due to the lack of relevant information in the data. Large urban areas have a higher share of non-vehicle owners due to among other things better access to public transit (Baum-Snow and Kahn 2005).

where $n_t(\iota)$ represents the number of non-owners of type ι. The equation shows that new vehicle sales come from two sources, vehicle-owners who have scrapped their vehicles and decided to purchase a new one and non-owners who decide to change their vehicle ownership status. For vehicle owners, we aggregate over all vehicle ages, types and the owners' idiosyncratic income to obtain new vehicle sales.

Now we describe the evolution of $n_t(\iota)$ to complete the characterization of the evolving distribution. The distribution of non-owners evolves as follows,

$$\begin{aligned} n_{t+1}(\iota) &= \sum_{i=1}^{J}\sum_{a\geq 1}\left[\mu_{i0}^{r}(\iota, a, \mathbf{\Omega}_i, \mathbf{S}_t)\, \widehat{G}_t(\iota, a, \Omega_i)\right] \\ &\quad +\mu_{00}^{n}(\iota, \mathbf{S})\, n_t(\iota). \end{aligned} \tag{12}$$

As shown in the above equation, we aggregate over all vehicle ages and types to take into account all decision makers who decide not to own any vehicle.

Given the initial distribution $G_0(a, \Omega_i), n_0(\iota)$, and the assumed initial distribution on household type and idiosyncratic income, we can use equations (10) to (12) to derive the evolving distribution of observables over time. For any given year, we can obtain the distribution over observed vehicle characteristics by integrating over unobservables. Specifically, $G_t(a, \Omega_i)$, the distribution of vehicle age and characteristics (type and fuel economy) in year t is given by,

$$G_t(a, \Omega_i) = \sum_{\iota=0}^{1}\left\{\widehat{G}_t(\iota, a, \Omega_i)\right\}, t > 0. \tag{13}$$

4 Econometric Implementation

In this section, we describe our empirical strategy. We divide all the parameters into three sets. The first set of parameters, $\{\beta, N, \overline{\pi}\}$, are parameterized to their conventional values. Each period in the model represents one year, we thus set β to 0.95. We set the maximum life span of vehicles, N, at 35.[11] We set $\overline{\pi}$, the scrap value of a vehicle in the absence of the subsidy program to \$500 in the benchmark case and conduct robustness checks with it being set to zero.

The second set of parameters are either calibrated or estimated without resorting to the

[11]We assume that the value to the owner of a vehicle in its 35th year becomes $\overline{V}^{n}(\iota, y, \mathbf{S})$.

structural model. The third set of parameters include the preference parameters and are the focus of our paper. They are estimated using the non-linear least square method to minimize the distance between observed data and model predictions. We now describe the latter 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: (i) those governing the dependence of vehicle miles of travel upon vehicle characteristics; (ii) those governing the dependence of new vehicle prices upon vehicle characteristics; and (iii) those govern the exogenous processes of $\{Y_t, O_t, P_t\}$, the three aggregate state variables.

4.1.1 Parameters Determining Vehicle Miles of Travel

The gasoline expenditure on a vehicle is equal to vehicle miles of travel (VMT) in a given period multiplied by the gasoline cost per mile, $O_t x$, which is the product of gasoline prices O_t and gpm x. We assume that VMT in a given period is an exponential function of the gasoline cost per mile, that is,

$$VMT = \tau (a, g) (O_t x)^{\eta}, \tag{14}$$

where the coefficient $\tau (a, g)$ 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, $F (a, g, x, O_t)$, the total gasoline expenses for driving a vehicle with characteristics $\{a, g, x\}$, is given by $\tau (a, g) (O_t x)^{\eta+1}$.

Equation (14) specify the relationship between VMT and the fuel cost of driving. The parameters to be determined in equation (14) include η and parameters involved in $\tau (a, g)$. 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 $\tau (a, g)$ takes the following form:

$$\tau (a, g) = \tau_{1,g} a^{\tau_{2,g}}. \tag{15}$$

Given gasoline cost per mile, the parameters $\tau_{1,g}$ and $\tau_{2,g}$ determine vehicle miles of travel for given vehicle type and age. These two pairs of parameters are estimated in Lu (2006) based on VMT data by vehicle type and age:

$$\tau_{1,1} = 1.8, \tau_{1,2} = 2.1, \tau_{2,1} = -0.2877, \tau_{2,2} = -0.3130.$$

4.1.2 Parameters Determining New Vehicle Prices

In order to capture the differences in prices of new vehicles with different types and fuel economy, we assume that

$$P_{g,x,t} = \varsigma_g P_t \left(\frac{x}{\overline{x}_g}\right)^{\kappa_{g,x}}, \tag{16}$$

where $P_{g,x,t}$ denotes the full price of a type-g new vehicle with gpm x. $\overline{x}_g$ represents the average gpm of type g vehicle. The coefficient $\kappa_{g,x}$ captures the relationship between fuel economy and new vehicle prices. We allow $\kappa_{g,x}$ to differ by type and whether the vehicle is above or below the average gpm of the same type. The parameter ς_g captures differences in the average prices of passenger cars and light trucks.

We estimate the relationship between new vehicle prices and vehicle characteristics specified in equation (16) outside the model. In our model, vehicles are characterized by age, type and fuel economy. In the data, however, vehicles also differ along other dimensions, such as horsepower, acceleration and quality. Our modeling choice of abstracting away from other characteristics is largely dictated by the need to economize on the state space and the fact that these three variables do a good job in characterizing vehicle scrappage as we show in Table 3 and Section 5.1.

To obtain the estimates of κ, we estimate a hedonic price function on vehicle type, gpm based on (virtually) all new vehicle models sold in the U.S. from 1998 to 2005. For cars, the estimates of κ are 0.87 and 1.10 for those with gpm less than 0.0417 (the average gpm of cars) and for those with larger gpm, respectively. For light trucks, the estimates on κ for those with gpm less than 5.35 (the average gpm of trucks) and for those with larger gpm, respectively.[12] We set ς to be one for cars and 1.07 for light trucks based on the price data.

[12]The dependent variable is the logarithm of average retail prices and log(gpm) enters on the right side. We also regress vehicle prices on fuel economy while controlling for other characteristics including size and horse power. The coefficient for fuel economy becomes negative, implying that holding other features the same, the more fuel efficient a vehicle is, the higher the price is.

4.1.3 Transition Dynamics of Aggregate State Variables

Before conducting the simulation, we first specify stochastic processes for the three aggregate state variables: income, gasoline price, and vehicle price. We assume that these variables follow a VAR(1) process.

$$\begin{bmatrix} Y_t \\ O_t \\ P_t \end{bmatrix} = \begin{bmatrix} \mu_Y \\ \mu_o \\ \mu_p \end{bmatrix} + \begin{bmatrix} \rho_{yy} & \rho_{yo} & \rho_{yp} \\ \rho_{oy} & \rho_{oo} & \rho_{op} \\ \rho_{py} & \rho_{po} & \rho_{pp} \end{bmatrix} \begin{bmatrix} Y_{t-1} \\ O_{t-1} \\ P_{t-1} \end{bmatrix} + \begin{bmatrix} e_{Yt} \\ e_{ot} \\ e_{pt} \end{bmatrix}, \tag{17}$$

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

$$\Sigma = \begin{bmatrix} \omega_{yy} & \omega_{yo} & \omega_{yp} \\ \omega_{oy} & \omega_{oo} & \omega_{op} \\ \omega_{py} & \omega_{po} & \omega_{pp} \end{bmatrix}. \tag{18}$$

Since these processes are exogenous to the household, we estimate the parameters in the first three equations outside of the dynamic optimization problem in order to reduce the computational burden. Based on the data on average household income, gasoline prices, and new vehicle prices from 1967 to 2008, we estimate a VAR(1) process for these three 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.

4.2 Estimation of Key Parameters

The focus of our estimation strategy is the parameters in the contemporaneous utility function and the parameters governing consumer types in equations (2) and (8) including $\phi_{0,g}$, $\phi_{1,g}$, $\phi_{2,g}$, $\phi_{3,g}$, α_k, ξ, γ, where g is vehicle type. We estimate them based on the cross-sectional distribution of vehicles (i.e., vehicle registration data) at the vintage-nameplate (i.e., model) level in 2000, 2005 and 2008. The estimation strategy is to find the parameter vector that can best match observed vehicle registration data to their simulated counterparts through weighted nonlinear least squares (WNLS).

Conditional on observed state variables, pre-calibrated and pre-estimated parameters, and a given set of the key parameters, our model can generate annual survival rates for each vintage-nameplate characterized by age, type and fuel economy . Given the registration data in 2000, those survival rates lead to predictions of remaining registration in 2005 for each vintage-nameplate. Similarly, the registration data in 2005 can be used as a starting point to predict the remaining registration in 2008. In addition, our model can predict sales of new vehicles in each year by type and fuel economy. Together these predictions generate cross-sectional distribution of vehicles by age, type and fuel economy separately in 2005 and 2008. The objective function is defined to minimize the sum of differences between the predicted and observed data on vehicle registration including both new and used vehicles in 2005 and 2008.

Define θ as the set of key parameters to be estimated, the objective function is

$$\mathcal{J}(\theta) = \frac{1}{\mathrm{I}_1} \sum_{i=1}^{\mathrm{I}_1} \frac{\left[\widehat{q_{i5}}(\theta) - q_{i5}\right]^2}{\widehat{\sigma_i^2}} + \frac{1}{\mathrm{I}_2} \sum_{j=1}^{\mathrm{I}_2} \frac{\left[\widehat{q_{j8}}(\theta) - q_{j8}\right]^2}{\widehat{\sigma_j^2}}. \tag{19}$$

where the first part of the objective function is based on predictions errors for the cross-sectional distribution in 2005 and the second part is for 2008. I_1 and I_2 are the total number of vehicle models in 2005 and 2008, respectively. i and j are indices for for vehicle models. q_{i5} is the number of registrations of model i in year 2005 observed in the data and q_{j8} is the number of vehicles of model j in year 2008. $\widehat{q_{i5}}(\theta)$ is the predicted number of registrations for model i in year 2005 and the prediction is given by:

$$\widehat{q_{i5}}(\theta) = \begin{cases} q_{i0} \prod_{t=1}^{5} s_{it}(\theta), & \text{if model } i \text{ existed in year 2000} \\ \widehat{q_i}(\theta) \prod_{t=k,k>1}^{5} s_{it}(\theta), & \text{if model } i \text{ is of vintage 2001 to 2004} \\ \widehat{q_i}(\theta), & \text{if model } i \text{ is of vintage 2005.} \end{cases} \tag{20}$$

where q_{i0} is observed registration of model i in year 2000. $s_{it}(\theta)$ is the survival rate of vehicle i in year t during 2001 to 2005. The survival rate is determined by the probably of keeping the vehicle for a certain type ι in (5) and the type probability which is updated based on the initial type distribution in (8). $\widehat{q_i}(\theta)$ is the predicted vehicle sales when model i enters the market during 2001 to 2005. It is determined by new vehicle purchase probabilities among both vehicle owners and non-owners. $\widehat{q_{j8}}(\theta)$ is the predicted number of registrations for model j in year 2008 and it is defined similarly to $\widehat{q_{i5}}(\theta)$. $\widehat{\sigma_i^2}$ and $\widehat{\sigma_j^2}$ are the fitted values of the variance of heteroskedastic errors. These are obtained based on initial parameter estimates from nonlinear least squares.

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.[13] In each period, the pool 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. The type distribution among non-owners is updated accordingly based on the distribution in the previous period and consumer types (ι) of those who newly enter and exit the pool.

5 Estimation Results

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

5.1 Parameter Estimates

Before presenting parameter estimates from the structural model, we first present estimation results from reduced-form OLS regressions of vehicle scrappage rate 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 our modeling strategy of the structural estimation and help us interpret the estimation results from the structural estimation.

Panel 1 of Table 3 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. This suggests that the three vehicle characteristics (age, gpm, and type) used

[13] 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 to this.

in the dynamic model can capture well the variations in vehicle scrappage. Panel 2 of Table 3 shows the results for the 3-year scrappage rate from 2006 to 2008. The results are qualitatively the same as those in panel 1. In both panels, the coefficients on interactions terms containing car dummy are all statistically significant from zero. In the structural model, we allow different parameters for these two types of vehicles as well.

We now turn to the estimates of the key parameters in the structural model as specified in equations (2) and (8). Table 4 presents coefficient estimates and their standard errors for four specifications. The first specification assumes no consumer preference heterogeneity on fuel economy while the other three allow preference heterogeneity. The first two specifications do not allow borrowing and consumers have to pay the full purchase cost of new vehicles up-front. The last two specifications allows borrowing by assuming that all consumers take a five-year auto loan with a fixed interest rate of three percent.[14] The fourth specification sets the scrappage value of a vehicle to be zero while the first three specifications use \$500 as the scrappage value. We estimate these four specifications to examine how robust our findings are to heterogeneity, borrowing, and the scrap value.

Panel 1 in this table contains estimates of preference parameters in the contemporaneous utility function. Most of the parameter estimates across specifications are intuitively signed and statistically significant. The estimate of the risk aversion parameter, γ, is larger than zero in all specifications, implying that households are risk averse. Our estimates of γ fall between 2.05 and 3.037, well within the region considered reasonable by the literature.[15] The second coefficient captures the utility from keeping the status quo (relative to making changes in vehicle ownership) and its estimates are all positive and significant across the specifications. The coefficient estimates on log(age) and its quadratic term for both cars and light trucks imply that for vehicles less than four years old, the utility is rather flat with

[14] Specifically, we define $P_{avg,g,x}$ as the average price of vehicles of type g and with gpm at x. We assume the following auto-loan terms: in order to purchase a new vehicle, a household has to provide the down payment at $P_{g,x,t} - 0.8P_{avg,g,x}$ at the periods of purchase, and pay out the rest in five equal installaments in the first year and the following four years. The amount of installment is calculated so that the present value of installments is equal to $0.8P_{avg,g,x}$ at a 3% interest rate. We adopt this particular auto-loan structure to economize on the number of state variables. For example, since installments are constant and the down payment is the only part of payment which varies with the state variables, we do not have to keep track of vehicle prices at the time of purchases in computing installments. Such a structure allows for auto loans under specific terms but not other forms of loans, thus we do not need to carry household wealth as a state variable.

[15] The estimate of the risk aversion parameter, γ, is widely dispersed. However, as indicated by Chetty (2006), "Most economists believe based on introspection that $\gamma \in (1, 5)$, while others contend higher values of gamma are reasonable".

respect to age but for older vehicles, consumers derive less utility as vehicles age.

The coefficient estimates on log(gpm) are positive, implying that consumers prefer fuel-inefficient vehicles (large gpm) *holding other factors such as driving costs constant.* As we discussed above, the fuel economy variable affect utility through two channels: the flow utility, and the driving cost. We do not include other vehicle attributes such as vehicle size and horsepower in the model in order to economize on the state space. The positive coefficient on log(gpm) reflects that the fuel economy is used as a catch-all variable attribute in the flow utility and that fuel-efficient vehicles tend to be smaller vehicles with less horsepower. It is important to note that our model allows fuel economy affects utility through the fuel cost of driving and the consumption of the numeraire good: more fuel-efficient vehicles incurs lower fuel costs and thus leave owners a higher level consumption of nondurable goods. The simulations below based on parameter estimates show that when gasoline prices go up, the market share of fuel-efficient vehicles goes up. The second channel captures the real impact of fuel economy itself on consume choices and our policy analysis relies only on the second channel. For specifications 2-4, we allow for heterogeneous preference of two types. The difference in the coefficient on log (gpm) between the two types is given in the second to the last row of panel 1. The estimated differences are positive and significant in all three specifications, justifying the flexibility of allowing for heterogeneity in households preferences.

The last row provides the estimates for the aggregate preference parameter that affects intratemporal substitution between auto services and nondurable consumption. The estimated values of the risk aversion parameter, γ, and the aggregate taste parameter, ξ, are higher in specifications 3-4, when borrowing is allowed. The relative magnitudes of these two estimates compared to their counterparts in specifications 1-2, the cases of no borrowing, make intuitive sense. Since allowing for borrowing makes it relatively cheaper in pecuniary terms to purchase a vehicle, had the estimates of γ and ξ remained the same as in the case of no borrowing, the model would predict larger vehicle sales than those observed in the data. Therefore, the estimates of γ and ξ have to be higher so that the loss in terms of marginal utility of consumption from purchasing a new vehicle would compensate for the reduction in pecuniary costs. In addition, the estimated value of the utility gain from keeping the status quo, α_k, is higher in the case of borrowing. An increase in the estimated value of α_k also serves to dampen the effect of the reduction in pecuniary costs on the households' incentives to purchase new vehicles.

Panel 2 of Table 4 presents the parameter estimates that determine the initial type distribution of vehicle owners (those who owned a vehicle in the beginning of our data period). As shown in equation (8), we assume that the type distribution follows a logistic function. The negative coefficient estimates on gpm suggest that those who owned less-efficient vehicles are less likely to be of low type (i.e., those who value gpm less). Under the second specification, the parameter estimates imply that about 86 percent of vehicle owners in year 2000 are of low type and the rest are of high type. Under the third and fourth specifications, the share of lower type consumers is estimated to be about 41 percent among vehicle owners in year 2000.

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 in the data.

Figure 4 plots the survival rate 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 in specification 3 in Table 4 which allows for preference heterogeneity and borrowing while 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. The match not being as good for older vehicles is likely driven by larger variations in observed survival rates from fewer registrations per model. In addition, our assumption on the maximum life span of 35 years may explain partly why the predicted survival rates for old vehicles are lower than those observed.

Figure 5 plots predicted *cumulative* survival rates by type and age as implied by the estimates from specification 3. For each vehicle type, we categorize low mpg vehicles as those above the median level of gpm. Those survival rates are obtained by averaging across all the other observed state variables based on the weights by age and type, and the invariant distribution for aggregate state variables. Within each vehicle type, low mpg vehicles (e.g., those that are larger and with more horsepower) have higher survival rates than high mpg vehicles, consistent with the pattern in Figure 2 and the OLS results in Table 3. In addition, based on vehicle inventory data, ARB (2004) estimates that 50 percent of vehicles survive up to 15 years while 25 percent of vehicles survive up to 20 years. The magnitude of cumulative survival rates implied by our model is in line with those estimates.

We now examine how gasoline prices and household income affect vehicle choices based on our model estimates. Figure 6 plots the conditional probability of choosing low mpg vehicles ($\leq$ 19 for cars, $\leq$ 14.5 for trucks) versus high mpg vehicles by the households who are strongly (high type) and weakly (low type) averse to vehicle fuel economy. The choice probabilities are conditional on the households choosing to purchase a new vehicle and are averaged across the long-run distribution of household income and vehicle prices.

The two graphs on the left column of Figure 6 shows how choice probabilities respond to changes in gasoline prices. As gasoline prices increase, the probability of choosing high mpg vehicles (both cars and trucks) increases, while the probability of purchasing low mpg vehicles decreases. While the pattern holds true for both types of consumers, households which are strongly averse to vehicle fuel economy (high type) have a higher probability of choosing a low mpg vehicle at every given gasoline price level than low-type households.

The right column of Figure 6 depicts how choice probabilities respond to changes in household income. As household income increases, the probability of choosing high mpg vehicles (both cars and trucks) decreases, while the probability of purchasing low mpg vehicles increases. The pattern is even more salient for households who are averse to vehicle fuel economy (high type). Given that low mpg vehicles are more expensive in our model, higher income relaxes the household's budget constraint to purchase vehicles of lower mpg, with the impact stronger on households who strongly prefer low mpg vehicles.

6 Policy Analysis

Our model estimation and the quantitative analysis above assume a constant scrap value across vehicle models. Under scrappage subsidy programs, the scrap value could differ according to the characteristics of the trade-in and new vehicles. This could in turn affect household choices of vehicle purchase and fuel economy. In this section, we conduct policy analysis based on our parameter estimates to analyze the cost-effectiveness of different designs of the CFC program. The goal is to understand how the elements designed for environmental consideration affect the effectiveness of the CFC as a stimulus program.

6.1 Policy Alternatives

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 cannot replicate the program as it exactly happened. Instead, we examine a hypothetical program that has the same key eligibility rules but with a duration of one year in 2009. We define this as our benchmark policy as opposed to the alternative policy 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.

There is one minor difference between the above rules and those in the real CFC program. For all light trucks, we adopt the 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. Since most light trucks are category one trucks, this difference is likely to be inconsequential to our qualitative conclusion.

In order to investigate the tradeoff between the stimulus and environmental objectives, we compare the outcomes from the benchmark policy with those from an alternative policy. The alternative policy removes the last two requirements that are specifically designed to achieve larger environmental benefits. That is, rather than requiring the mpg of the new vehicle to be higher than that of the trade-in vehicle by certain levels, the alternative policy does not have any mpg requirement on new vehicles and the subsidy is the same for all eligible transactions.[16]

[16]This is also the major difference between the CFC program as implemented and that outlined by Alan Blinder in his New York Times article. Although he suggested similar eligibility rules for trade-in vehicles, his proposal does not include requirements on new vehicles.

6.2 Counterfactual Simulations

We start with the vehicle population profile in 2008 and simulate changes in vehicle population through new vehicle sales and scrappage in 2009 and onward till 2033 under three scenarios: without CFC, the benchmark policy, the alternative policy. To make the policies comparable, we adjust the level of subsidy under the alternative policy 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 vehicle sales and environmental benefits.

We estimate the environmental benefits from two parts. The first part is the benefit from the reduction in CO_2 emissions. We calculate gasoline consumption and CO_2 emissions under various scenarios based on the simulated fleet characteristics and VMT. We follow the VMT schedule over vehicle lifetime from Lu (2006) where annual VMT decreases over vehicle age for passenger cars and light trucks separately. Based on the 2001 National Household Travel Survey, the average lifetime VMT is estimated at 152,137 for a car and 179,954 for a light truck. The benefit from the reduction in CO_2 emissions is 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 with 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 computer program maintained by 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).

Figure 7 shows the comparison in new vehicle sales (top graph), gasoline consumption (middle graph), and environmental benefits (bottom graph) from 2009 to 2033 under the no-policy scenario, the benchmark policy, and the alternative policy. These simulations are based on the third specification in Table 4 which allows preference heterogeneity on fuel economy and borrowing. The simulations based on other specifications produce very similar patterns and will be further discussed in the next section. To ease exposition, the outcomes in the no-policy scenario are normalized to zero and only differences across policy scenarios are shown. The top graph shows that the benchmark policy would have increased new vehicle sales in year 2009 but reduced sales in the future, consistent with a demand pull-forward. The alternative policy would produce a larger increase in vehicles sales, suggesting a larger stimulus outcome.

The middle graph depicts the reductions in gasoline consumption from the benchmark policy and the alternative policy relative to the no-policy scenario. The largest reduction occurred in 2009 and the reduction would diminish over time. This is because the low-mpg clunkers would have been gradually replaced over time even without the policy, implying that the vehicle fleet would become similar over time under the policy and no-policy scenarios. The benchmark policy would result in larger reductions in gasoline consumption than the alternative policy because new vehicles sold under the benchmark policy in 2009 would be more fuel efficient. The bottom graph in figure 7 shows the environmental benefits in monetary terms coming from reductions in CO_2 emissions and four criteria pollutants. The environmental benefits would be largest in 2009 and decrease over time. The benchmark policy, with requirements on the minimum mpg of new vehicles, would produce large environmental benefits than the alternative policy.

6.3 Cost-Effectiveness Comparison

The graphs in Figure 7 show while both policy designs would stimulate new vehicle sales and improve the environment, there is a tradeoff between the two outcomes. In particular, the benchmark policy would achieve large environmental benefits but a weaker stimulus outcome. We now examine and quantify the tradeoff. Table 5 shows aggregate policy outcomes and provides a metric for comparing cost-effectiveness of different policy designs. The four panels correspond to the four specifications in Table 4.

Outcomes under Benchmark Policy Panel 1 is based on the first specification without consumer heterogeneity or borrowing. The simulations show that the benchmark policy in 2009 would have seen 1.97 million eligible transactions with total program spending of \$7.97 billion, implying an average subsidy of \$4,000 per transaction. Among these eligible transactions, 0.53 million new vehicles would not have been sold without the policy. These induced sales represent the true stimulus effect in auto demand in 2009. The second panel, based on the second specification in Table 4 with preference heterogeneity but without borrowing, suggests that the benchmark program would cost \$8.56 billion on 2.10 million eligible transactions, 0.57 million of which would not have happened during the program period without the program. Under the second specification, a large fraction of households (estimated at 86 percent in 2000) are of low type (less adverse toward fuel efficient vehicles) and they are more likely to conduct transactions deemed eligible by the benchmark policy, with or without the scrappage subsidy. Although households of high type are less likely to engage in eligible transactions, the increase in the number of eligible transactions by the low type more than offset the reduction among the high-type households.

The simulations based on specifications three and four show a smaller program size with total spending of \$6.13 billion and \$6.35 billion, respectively. The eligible transactions are 1.53 and 1.59 million, while the induced sales are 0.27 and 0.32 million units. The smaller number of eligible transactions is a direct result of larger estimates of risk aversion and aggregate taste parameters. A larger estimate of either of these two parameters implies a higher marginal utility of consumption, thus raising the marginal sacrifice incurred by purchasing a new vehicle.

The simulation results for the benchmark policy seem plausible in comparison with those from the CFC program in reality. 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. Li, Linn and Spiller (2012) estimate that among the eligible transactions, about half of the eligible sales or 360,000 units were induced by the program during the one-month period using a difference-in-differences approach. Mian and Sufi (2011) obtain almost identical results based on a different data set. Both studies suggest that the majority of these included sales were sales that would have occurred in the next few months hence the stimulus effect dissipated quickly. Our simulations from the four specifications suggest that the share of induced sales account for about 20 to 25 percent of the eligible sales. Given that our program is one year instead of one-month, it is reasonable to argue that the share of induced sales would be smaller.

The total environmental benefits from 2009 to 2033 are predicted to be 0.53 and 0.39 billion dollars under the first two model specifications. Under the last two specifications, they are 0.31 and 0.36 billion dollars. In order to evaluate the cost-effectiveness of the program, we net out the environmental benefits from the total spending and obtain a measure of unit cost for the stimulus, government spending per unit of induced sales, in the last column. The results from the first specification imply that the net unit cost of stimulus is \$14050, as much as the price of a subcompact car. The unit cost is even higher under the other three specifications. The higher unit cost in those specifications reflects that buyers who are highly averse to fuel efficient vehicles are not swayed by the benchmark policy, while most of the buyers who are weakly averse to such vehicles would purchase a new vehicle even without subsidies. The estimates of high unit costs underscore the common challenge in designing a cost-effective scrappage program, that is, screening out the households which would purchase a new vehicle regardless of scrappage subsidies.

Outcomes under Alternative Policy As shown in the graphs in Figure 7, the alternative policy without any mpg requirement on new vehicles would lead to larger stimulus impacts but smaller environmental benefits. After netting out the environmental benefits, the alternative policy under the first specification would incur a net cost of \$12149 for each unit of induced sales, compared with \$14050 from the benchmark policy. This comparison shows that the benchmark policy has a net unit cost that is 15 percent higher than the alternative policy without explicit environmental designs. The higher cost is driven by the fact that some program participants need to be compensated at a higher subsidy level than under the alternative policy in order for them to buy high mpg vehicles which otherwise are not preferred. As a result, the environmental benefits from these choices are overwhelmed by the higher cost (to the government).

The cost difference between the two designs is actually underestimated in the first specification due to lack of preference heterogeneity. The absence of preference heterogeneity with regard to fuel efficiency implies stronger substitutions between high and low mpg vehicles in response to policy incentives, as compared to those implied by the second specification with preference heterogeneity.[17] In other words, the first specification underestimates the compensation needed for households to switch from an otherwise preferred model (e.g., a

[17] In the specification without preference heterogeneity, the only source of heterogeneity comes from the i.i.d. idiosyncratic taste shocks. In a static framework such as a multinomial logit model, this will lead to the independence of irrelevant alternatives (IIA) property which implies unrealistic substitution pattern across vehicle models. Although the IIA property does not hold under the dynamic model because the value function enters the choice probabilities, the restrictive substitution pattern can still exist due to the lack of consumer heterogeneity.

low mpg vehicle) to alternative choices (e.g., a high mpg vehicle). Therefore, the first specification would underestimate the cost of altering household vehicle choices and hence the tradeoff between the stimulus and environmental objectives. Under the second specification with preference heterogeneity, the policy comparison is more salient: the net unit cost in the benchmark policy is 30 percent higher than the alternative policy.

We now turn to the policy comparison from simulations based on the last two specifications in Table 4 which relax consumer budget constraint by allowing for borrowing. Recall that the estimates of risk aversion and aggregate taste parameters under the third specification are larger than those from the first two specifications. This implies that households are less willing to make the substitution between the vehicle service and the numeraire good than those implied by the first two specifications. As a result, the benchmark policy under this specification would have smaller total impacts in terms of eligible sales and total spending than those under the first two specifications. Meanwhile, the net cost of stimulus of over $21000 per unit of induced sales is much higher due to the fact that larger compensations are required to change consumer choices. The alternative policy has a much smaller unit cost of about $13000 and the policy comparison implies a 64 percent increase in net unit cost under the benchmark policy relative to the alternative policy.

The last set of simulation results are based on the fourth specification in Table 4 that assumes zero scrap value without participating in the scrappage program, versus $500 in the third specification. This would imply the scrappage subsidies are more appealing so the benchmark policy would generate more eligible sales and see a smaller unit cost ($18500 versus $21000). The unit cost of stimulus under the alternative policy is estimated to be $10500. The comparison between the policy designs suggests that the benchmark policy would incur 77 percent higher costs than the alternative policy without mpg requirement on new vehicles. Since the scrap value of a typical vehicle tends to fall into the range between zero and $500, the simulation results from these two specifications should provide bounds for the cost-effectiveness comparison between the two policy designs.

As discussed in the model section, our model assumes no second-hand market for computational purpose. This assumption is likely to lead to downward bias in utility from owning a vehicle since the assumption preclude trading before scrappage. This should manifest in downward bias in the parameter estimates on the constant terms for cars and trucks in the utility function, which captures the relative utility from buying a new vehicle versus not buying. In the meantime, there could be upward bias in the parameter estimates on keeping the status quo. In terms of their impacts on our findings from policy simulations, the downward bias in constant terms and the upward bias in keeping the status quo could both lead to under-estimation in demand stimulus and hence over-estimation in unit cost (i.e., the last column in Table 5). However, these bias should be present in both policy scenarios and it is unlikely that the policy comparison would be affected qualitatively.

7 Conclusion

In recent years, many countries have employed stimulus programs that are designed to achieve twin objectives: to stimulate the economy and to improve the environment. These green stimulus programs are especially appealing to policy makers and the public when global economic recession is intertwined with heightened concerns over the environment and climate change. During the 2009 G20 summit, the United Nations Environment Programme urged these countries to devote one percent of their GDP to green stimulus programs in an effort termed "A Global Green New Deal". While the overall effectiveness of green stimulus is still under debate, the common view is that the environmental benefits are co-benefits and hence additive to the stimulus objective.

In the context of the popular Cash-for-Clunkers program in the U.S., we provide a first empirical study to examine the tradeoff between the two objectives by estimating a dynamic discrete choice model of vehicle ownership using detailed national vehicle registration data. Based on parameter estimates, we conduct counterfactual analysis to examine stimulus and environmental outcomes under different policy scenarios. Simulations using various model specifications all point to a significant tradeoff between the two objectives: the design elements for the environmental objective can greatly undermine program effectiveness on stimulus. The benchmark policy that has the same key eligibility rules as the real CFC program would incur up to 77 percent higher costs for demand stimulus after netting out the environmental benefits than an alternative policy without design elements for the environmental objective (specifically mpg requirements on new vehicles). This finding is in contrast with the popular view on the relationship between stimulus and environmental benefits and should serve as a reminder of Tinbergen's rule on efficient policy design with multiple objectives. Although caution should be taken in generalizing our finding to other green stimulus programs, we believe that our framework of analysis can be adopted to examine other programs that focus on consumer demand such as subsidies on energy efficiency appliances as well as vehicle scrappage programs in other countries.

While policy makers in the U.S. and the international community at large have seen tremendous challenges in recent years in making progress toward dealing with climate change, government interventions with environmental goals such as green stimulus programs are increasingly adopted across the world. Although these programs are often purported as successful by policy makers, the cost-effectiveness of these programs remains largely unknown. Our study suggests that the cost of achieving the environmental objective from green stimulus programs such as the CFC program can be unduly high and such programs should not substitute for sound environmental policies such as the Pigouvian tax.

Two model assumptions that arise from computational concerns and data constraint deserve additional attention in future research. First, our model does not allow the second-hand market for used vehicles and this simplifies consumes' decisions. Incorporating the second-hand market would add liquidity to the value of owning a vehicle and thus impact new vehicle sales. Given that the second-hand market accounts for the majority of automobile transactions, future research is needed to fully understand their implications on our findings and on vehicle demand in general. Second, our model assumes that households can own at most one vehicle at all times. Since an average U.S. household owns close to two vehicles, accounting for decisions on the second vehicle in the household could be important. If household-level information on vehicle ownership is available, one can allow household decisions to be made on one vehicle in a given period while treating the attributes of the second vehicle as additional state variables. Nevertheless, allowing the second-hand market and simultaneous decisions on more than one vehicles would dramatically increase the computational burden due to the larger choice set and the increased number of state variables. In addition, these extensions would necessitate household level data that provide information on multiple vehicle ownership and how household demographics are linked with vehicle turnover.

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Table 1: Summary Statistics of Vehicle Population Profile

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
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	9.80198	63.963
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	9.80198	63.963
No. of registrations	19692	38462	1	663667

Note: The number of observations is 7464, 8720, and 10334 for 2000, 2005, and 2008 vehicle population profile, respectively. The mean and standard deviations of vehicle age, car dummy and mpg are weighted using the number of registrations. The oldest vintage in our data set is 1974.

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

	Eq1: Income		Eq2: Gas price		Eq3: Vehicle price	
Variable	Est.	S.E.	Est.	S.E.	Est.	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.674	0.963	0.589	1.638	1.034	0.458
Income	0.588	0.111	0.301	0.188	-0.138	0.053
Gas price	-0.098	0.068	0.840	0.116	-0.016	0.032
Vehicle price	0.445	0.233	-0.998	0.396	0.858	0.111

Error covariance	Income	Gas price	Vehicle price
Income	0.0131		
Gas price	-0.0066	0.0378	
Vehicle price	0.0023	-0.0068	0.0030

Note: The estimation is based on detrended data of average household income, annual gasoline price, and average vehicle price from 1967 to 2008. The variables are in 2008 dollars. The dependent variable in equation 1 (columns 1 and 2) is average household income; that in equation 2 (columns 3 and 4) is gasoline price; that in equation 3 (columns 5 and 6) is vehicle price.

Table 3: 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 4: Parameters from the Structural Model

Variables	No borrowing				Borrowing and Heterogeneity			
	No Heterogeneity		Heterogeneity		\$500 Scrap Value		Zero Scrap Value	
Variables	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.
	(1)		(2)		(3)		(4)	
Panel 1: Preference Parameters								
Risk averse parameter	2.050	0.305	2.819	0.334	3.037	0.321	3.026	0.320
Keeping the status quo	5.468	0.142	5.995	0.158	7.052	0.071	7.010	0.069
Constant for car	-0.118	0.189	-0.072	0.166	-0.167	0.093	-0.175	0.095
Log(age+1)*car dummy	0.679	0.052	0.677	0.057	0.448	0.059	0.451	0.060
Log(age+1)^2*car dummy	-0.210	0.010	-0.216	0.011	-0.177	0.009	-0.178	0.009
Log(gpm)*car dummy	0.182	0.013	0.112	0.020	0.099	0.020	0.102	0.020
Constant*truck dummy	0.081	0.179	0.190	0.160	0.739	0.111	0.726	0.111
Log(age+1)*truck dummy	0.396	0.043	0.392	0.048	-0.253	0.077	-0.246	0.077
Log(age+1)^2*truck dummy	-0.129	0.009	-0.130	0.010	-0.018	0.014	-0.020	0.014
Log(gpm)*truck dummy	0.144	0.014	0.013	0.021	-0.045	0.024	-0.042	0.024
Incremental taste for high types			1.181	0.093	0.203	0.023	0.197	0.023
Aggregate preference	13.077	4.585	38.106	13.993	80.594	37.673	78.699	36.553
Panel 2: Parmeters for consumer types								
Constant for owners			4.827	0.351	23.809	1.523	24.549	1.524
Log(gpm) for owners			-1.745	0.198	-15.011	0.862	-15.426	0.862

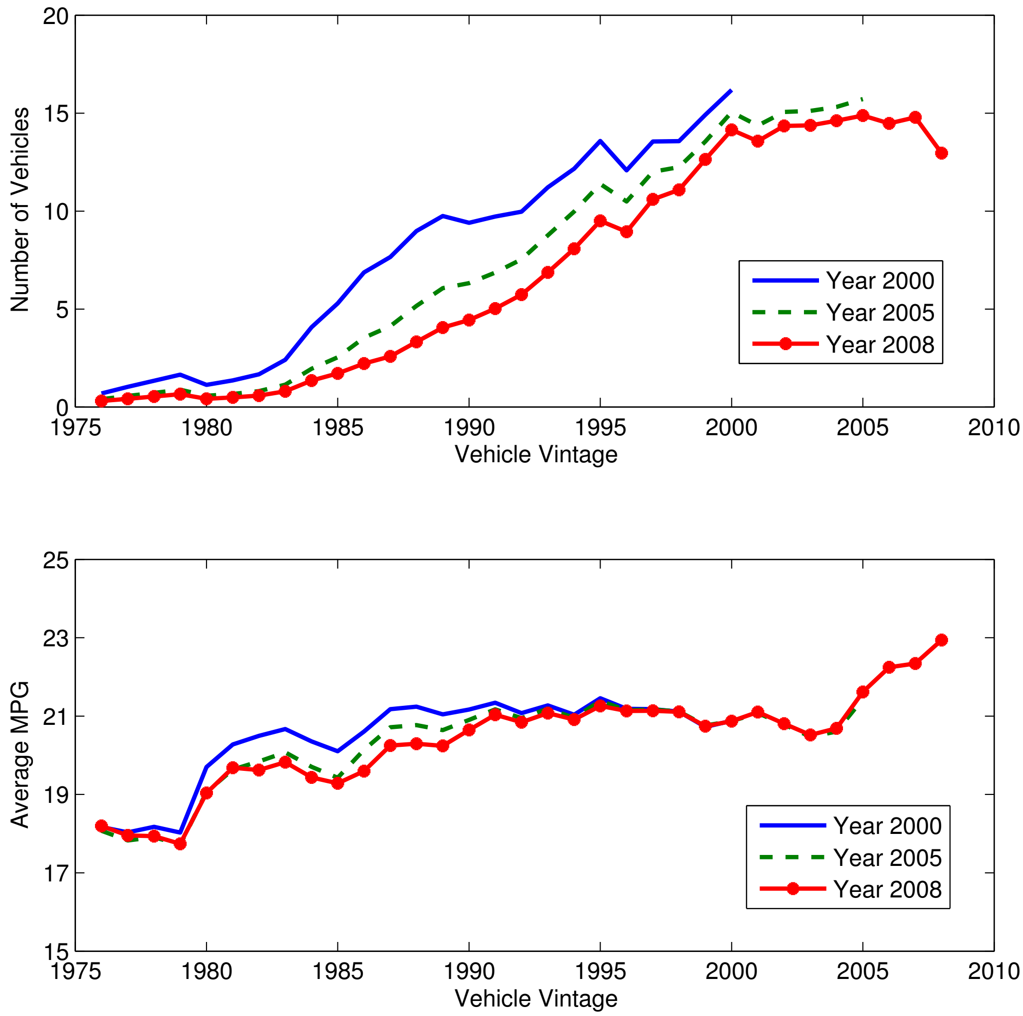
Note: The estimation results are from weighted nonlinear least squares. The first specification has no heterogeneity on consumer preference for log(gpm). The first two specifications do not allow for borrowing while the third and fourth specifications do. The first three specifications assume the scrap value for a used car to be \$500 and the last specification assumes it to be zero. The parameter for keeping the status quo captures transaction costs in vehicle replacement or purchase for owner and non-owners. The aggregate preference parameter ξ in equation (2) affects the intratemporal marginal rate of substitution between auto services and nondurable consumption. In the presence of taste heterogeneity (specifications 2-4), the preference parameter on log(gpm) for the high type is the corresponding parameter in rows 6 and 9 plus the incremental taste on log(gpm) in row 12. For vehicle owners in year 2000, the probably of being low type has a logistic form given in equation (8) and the coefficient estimates are given in the last two rows.

Table 5: Comparison of Alternative Policy Designs

Policy Scenarios	Spending ($billion) (1)	Environment ($billion) (2)	Eligible Sales (mil.) (3)	Increased Sales (mil.) (4)	$ per vehicle (5)
Specification 1: No Taste Heterogeneity					
Benchmark policy	7.97	0.52	1.97	0.53	14050
No requirement on new mpg	7.97	0.28	2.77	0.63	12149
Specification 2: Taste Heterogeneity					
Benchmark policy	8.56	0.39	2.10	0.57	14288
No requirement on new mpg	8.56	0.18	2.79	0.76	11044
Specification 3: Heterogeneity + Borrowing					
Benchmark policy	6.13	0.31	1.53	0.27	21395
No requirement on new mpg	6.13	0.15	2.52	0.46	13109
Specification 4: Heterogeneity + Borrowing + $0 scrap value					
Benchmark policy	6.35	0.36	1.59	0.32	18553
No requirement on new mpg	6.35	0.19	2.62	0.59	10500

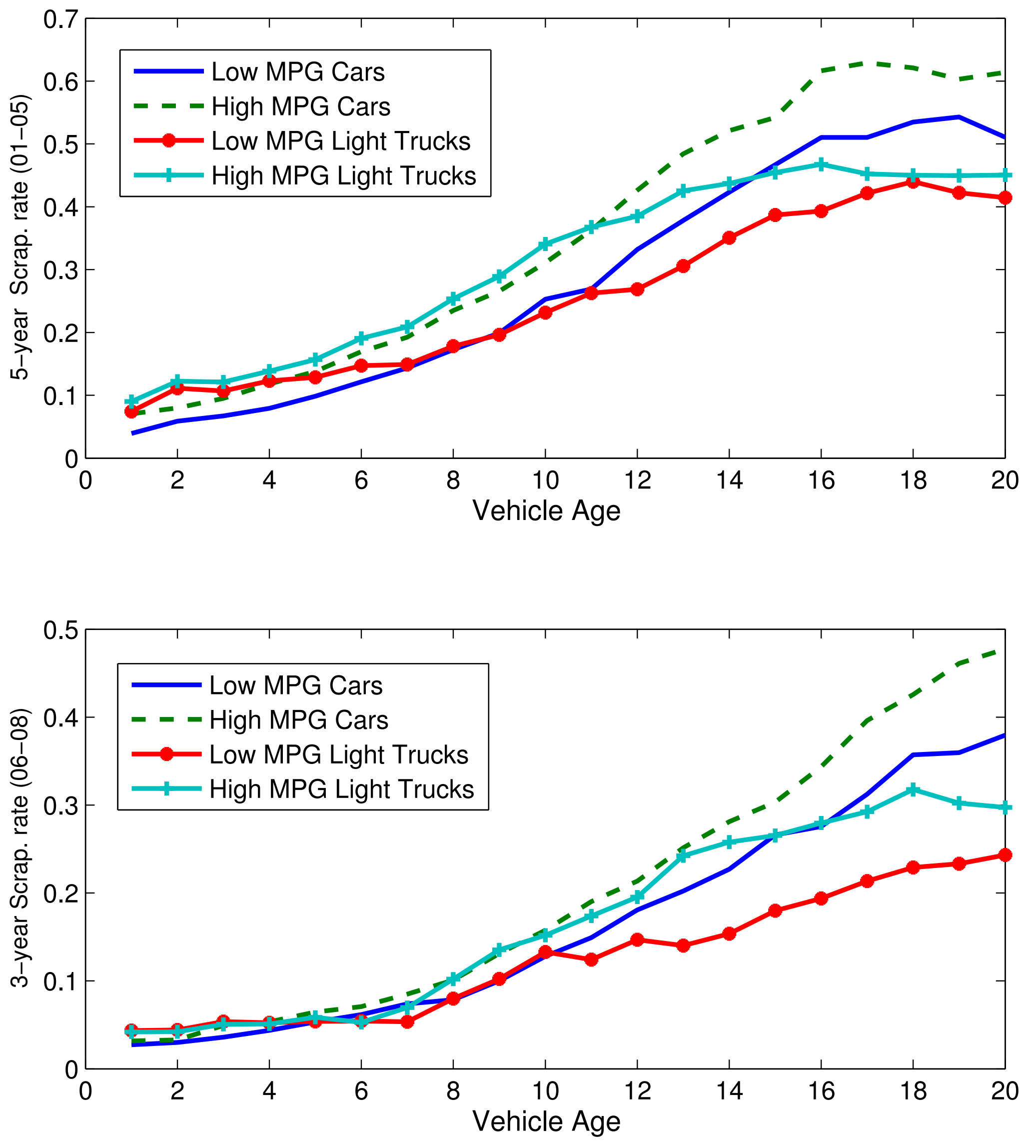
Note: The four specifications correspond to those in Table 4. The benchmark policy has the same key eligibility rules as in the real program lasted for about a month in 2009 but the benchmark policy has a duration of one year. The alternative policy has no mpg requirement on new vehicles. The subsidy level is chosen so that the total spending would be the same as that under the benchmark policy. The environmental benefits from the programs are avoided damages from reductions in CO_2 emissions and four criteria pollutants: carbon monoxide, volatile organic compounds, nitrogen oxides, and exhaust PM2.5. Increased sales in column (4) are the additional sales that would not have happened without the program. The last columned is the net unit cost of stimulus: government spending needed to increase one unit of vehicle sales netting out environmental benefits.

Figure 1: Vehicle Registration and Average mpg by Vintage



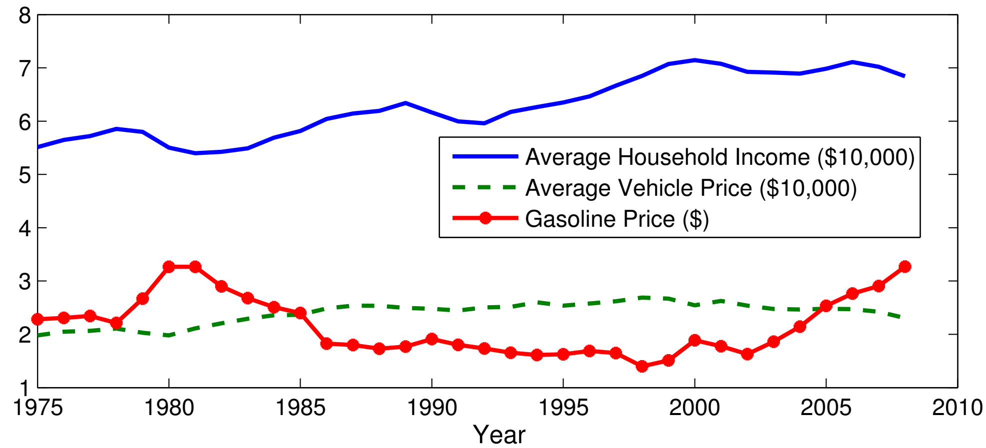
Note: The top graph shows the total number of passenger vehicles in the U.S. by vintage from 1976 in 2000, 2005, and 2008 from National Vehicle Population Profile. The bottom graph shows the average mpg of vehicles by vintage in 2000, 2005, and 2008.

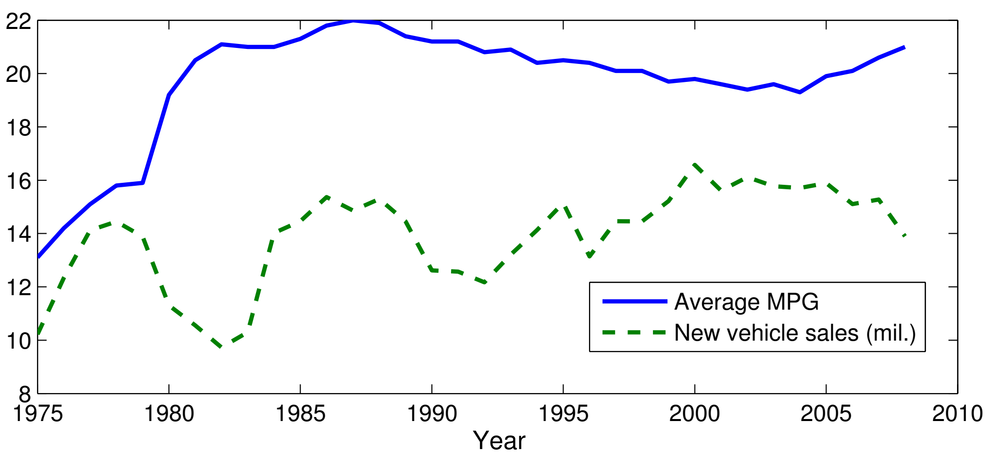
Figure 2: Scrappage Rate by Type and fuel economy during 2001-2005 and 2006-2008



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.

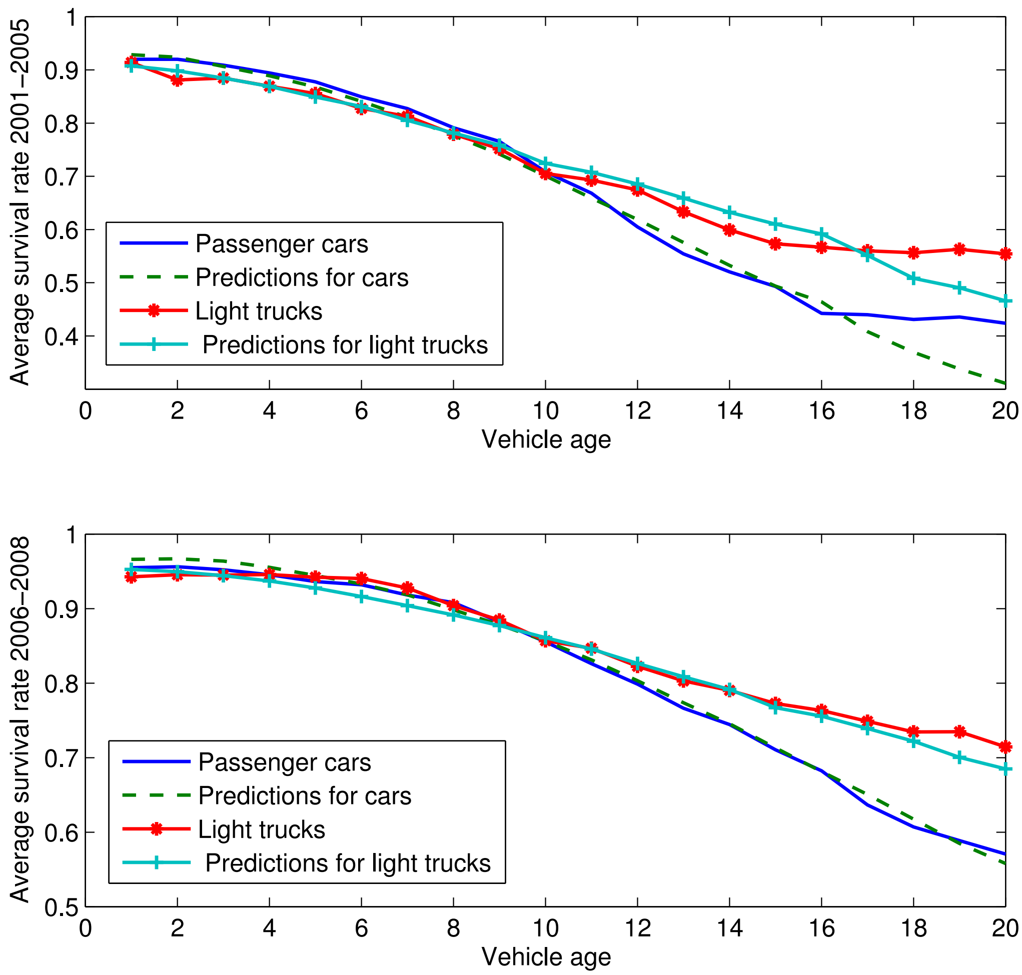
Figure 3: State Variables, New Vehicle Sales and Average mpg





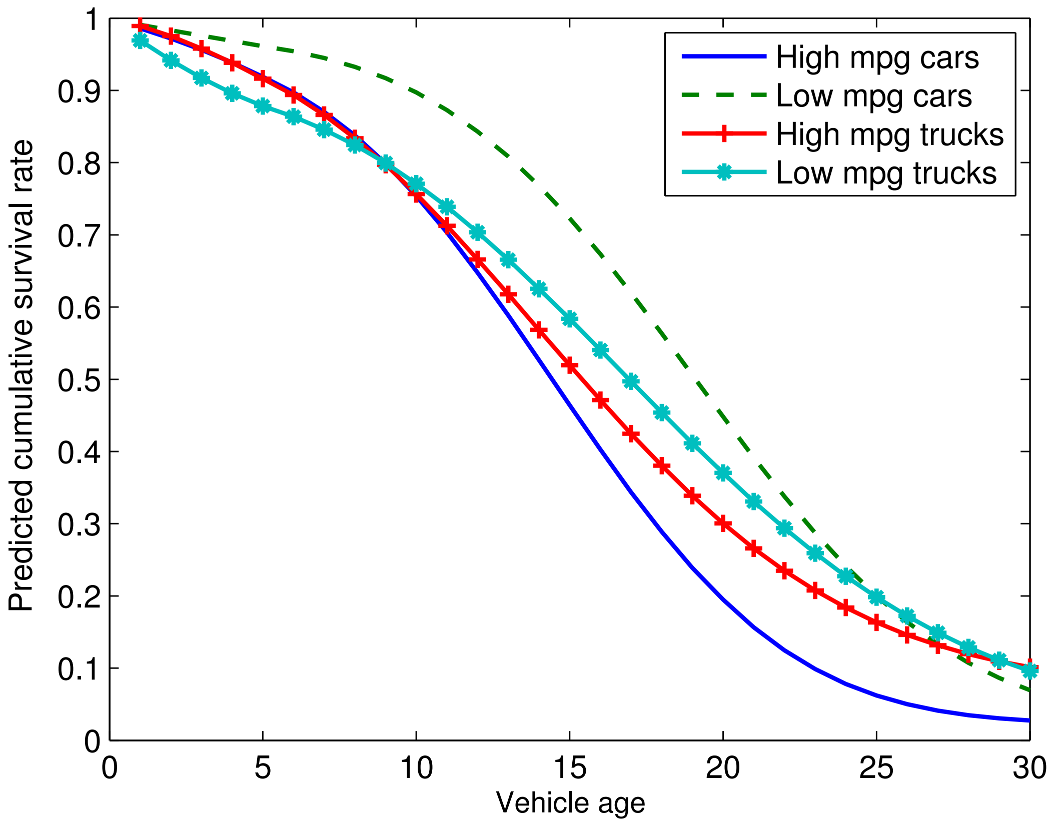
Note: The top graph shows average national household income, average vehicle price, and annual gasoline price in 2008 dollars. The bottom graph shows the total units of new vehicle sales and their average mpg.

Figure 4: Observed and Predicted Survival Rates by Age



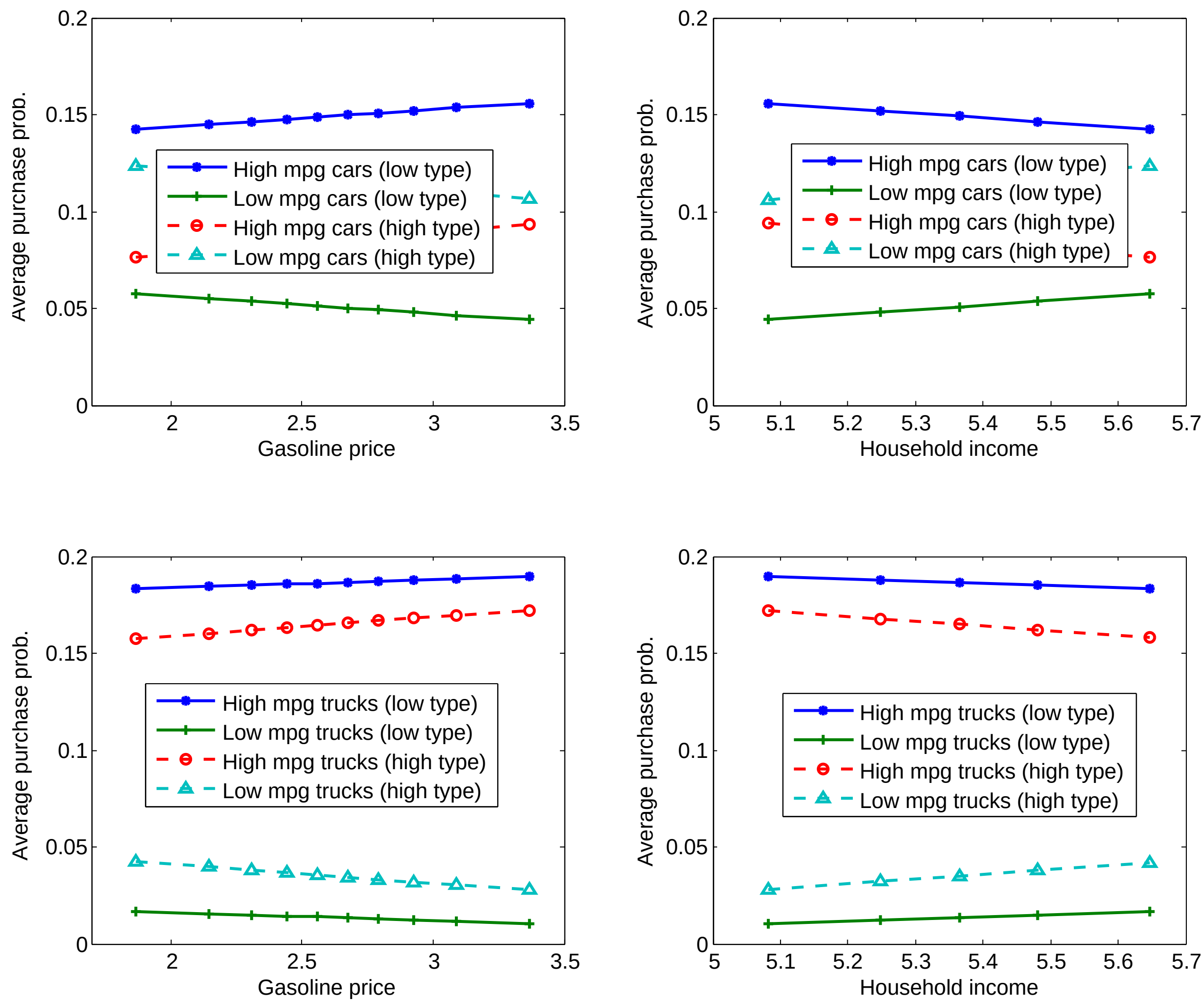
Note: The plots are based on the model estimates from specification 3 in Table 4. The top graph shows observed and predicted 5-year survival rates from 2001 to 2005 by vehicle type and age. The bottom graph shows observed and predicted 3-year survival rates from 2001 to 2005 by vehicle type and age.

Figure 5: Predicted Cumulative Survival Rates by Age



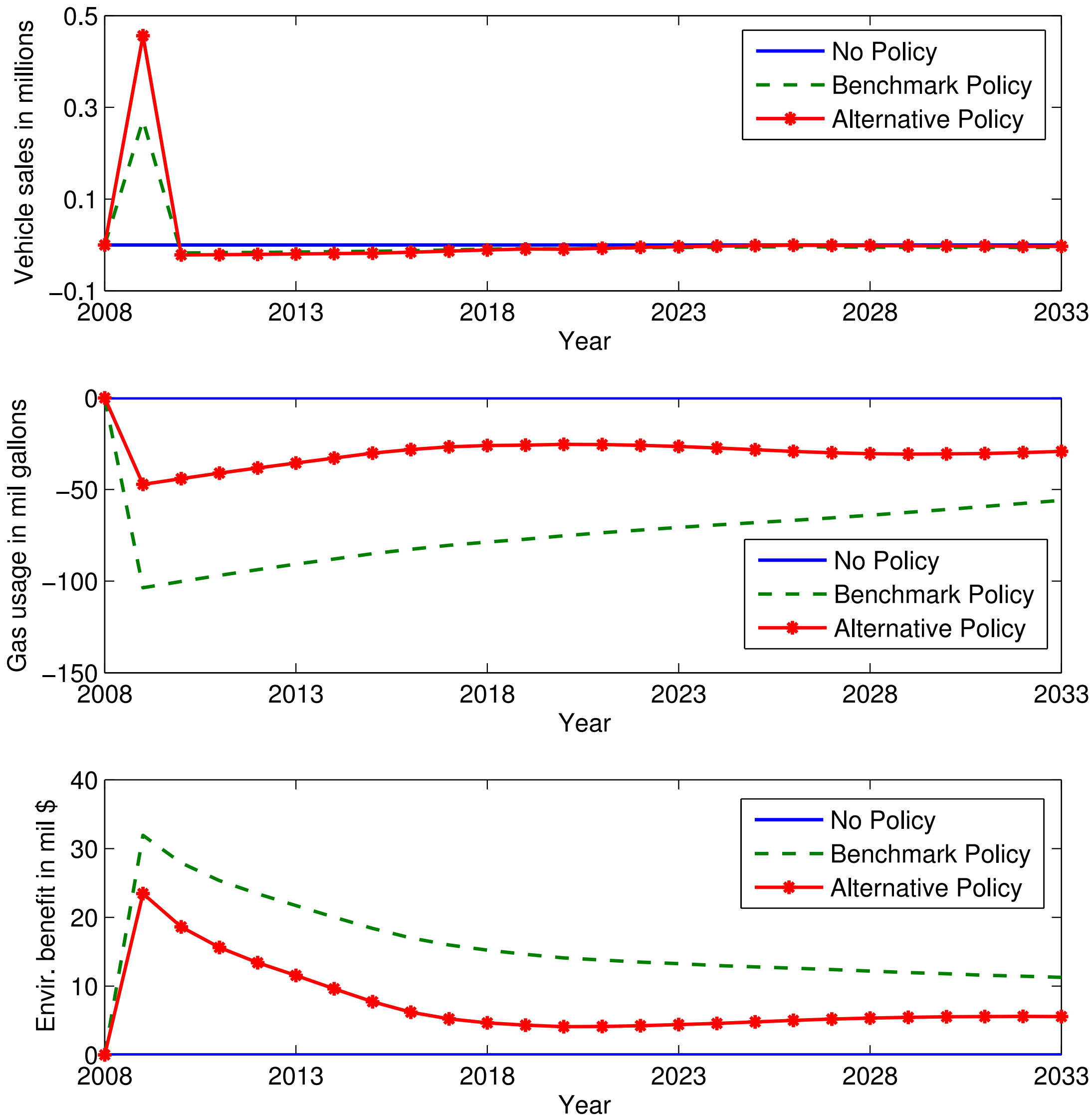
Note: The graph shows the cumulative survival rates by type and age predicted based on model estimates. Low mpg cars include passenger cars below the median mpg of all cars. Other categories are similarly defined. These survival rates are obtained by averaging over the eight observed states. The results based on the average over all 250 states are very similar.

Figure 6: Purchase probabilities of New Vehicles by Type



Note: The top left graph shows how gasoline price changes affect average purchase probabilities of low and high mpg cars change. The top right graph shows how household income affects purchase probabilities of low and high mpg cars . The two graphs on the bottom show how gasoline price changes and average income affect purchase probabilities of new trucks with different fuel economy. The low mpg cars are the cars with mpg lower than the median mpg of all cars. Low mpg trucks are similar defined. The purchase probabilities are averaged over the state space.

Figure 7: Policy Comparisons in Sales, CO_2 Emissions and Local Air Pollution



Note: The plots are based on the model estimates with preference heterogeneity on fuel economy . The top graph shows the effects of a benchmark policy and an alternative policy 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 does not have any requirement on the fuel economy of new vehicles. The middle graph depicts changes in gasoline consumption from the policies. The bottom graph shows the environmental benefits in dollar values from the reduction in CO_2 emissions and four criteria pollutants: carbon monoxide, volatile organic compounds, nitrogen oxides, and exhaust PM2.5.