Zwick Center for Food and Resource Policy

Working Papers Series

No. 2

Gasoline Prices, Fuel Economy Efficiency And Automobile Replacement Dynamics

Yizao Liu

November 2010

Department of Agricultural and Resource Economics

College of Agriculture and Natural Resources

1376 Storrs Road, Unit 4021

Storrs, CT 06269-4021

Phone: (860) 486-2836 Fax: (860) 486-2461

Contact: ZwickCenter@uconn.edu

University of Connecticut

Gasoline Prices, Fuel Economy Efficiency And Automobile Replacement Dynamics *

Yizao Liu
University of Texas at Austin

November, 2010

JOB MARKET PAPER

Abstract

This paper evaluates how gasoline prices influences the average fuel economy of the existing automobile fleet. Higher fuel price affects fleet composition in two ways: immediate purchase decisions of new, more fuel efficient, vehicles and scrappage of old fuel inefficient gas-guzzlers. Gasoline costs account for 65% of the total operating costs of driving an automobile. Rational forward-looking consumers will account for both current and expected future gasoline prices to decide not only what vehicle to purchase but also when to purchase it. Scrappage of old cars will also be driven by the same considerations, plus their increasing maintenance cost, and improved features of new models. In order to account for all these dynamic effects on the composition of the automobile fleet I specify and estimate a structural dynamic model of consumer demand for new and used vehicles as in Gowrisankaran and Rysman (2009). However, my model not only predicts the market shares of each vehicle sold in every period but also the survival probability for each model-vintage for each sample period. I estimate the model using a rich dataset combining vehicle registration and current fleet composition of several cities between 2003 and 2009 that include vehicle characteristics, price, gasoline price, and demographics for all market-years. Parameters are estimated by matching the predicted market shares and survival rates of every model-vintage with the corresponding empirical moments over the time span of the sample. Parameter estimates are then used to evaluate substantial fuel tax increases that have never been implemented before for being considered controversial and/or politically risky. Preliminary results for the Houston and San Francisco markets indicate that a permanent increase of gasoline price to $4 per gallon has stronger (and stable) long term effects than just doubling the current gasoline tax, which leads only to a temporary increase of the average fuel economy of the automobile fleet.

Keywords: Dynamic Demand Estimation, Gasoline Tax, Automobile Fuel Efficiency

*I am deeply indebted to Eugenio Miravete for his support and his effort for making the dataset available. I am very grateful to Kenneth Hendricks and Dean Corbae for their comments. I also benefited from comments of participants of I.O./Macro writing seminar. All errors are my own. E-mail: yizaoliu403@mail.utexas.edu

1 Introduction

In the United States, automobiles (passenger cars and light trucks) account for 60% of transportation energy use. Their dominance has made them a focus of efforts to improve fuel efficiency. Moreover, consumer's automobile demand is inherently dynamic. Unlike other durable goods, not all costs of vehicles will occur at the time of purchase, as gasoline and maintenance are needed to operate vehicles. In fact, gasoline is the most important ongoing expense during a vehicle's life-time use, accounting for over 65% of total operating costs.[1] A rational forward-looking consumer will take into account not only current but also future gasoline prices when facing the choice of purchasing a vehicle. With an anticipation of sky-rocketing gasoline prices in the future, consumers may want to switch to a more fuel efficient vehicle (for example, a Toyota Prius) by buying a new vehicle now and/or speeding the scrappage of old, inefficient gas guzzles. On the contrary, historically low gasoline prices may build an expectation of consistent low prices for consumers and lead to a surge in SUV and light truck sales.

Furthermore, the replacement decision of vehicles introduces another dynamic element of demand. As time goes by, consumers are not only confronted with an increasing cost of maintenance and depreciation of their vehicles as they age, but also with the choice of purchasing new and increasingly more efficient vehicles. New features of future vehicles, the optimal timing of scrapping old ones and the expectations on future gasoline prices determine the market shares of new vehicles sold and the compositions of the existing fleets of vehicles.

Estimation of consumer's dynamic demand for durable goods is difficult. Most empirical models of demand for durable goods have concentrated on the market for new products under a static setting. Berry, Levinshon and Pakes (1995), henceforth BLP, focuses on accommodating multiple dimensions of

[1] 2009 Your Driving Costs, AAA Association Communication

consumer heterogeneity in modelling the differentiated product demand for automobiles. However, BLP ignores the durability of products and emphasizes demand for new vehicle only. Esteban and Shum (2007) estimate a model of second-hand automobile market with forward-looking consumers and firms. They use a simple vertical model where consumers must purchase a car every period. However, their paper did not consider the scrappage and replacement decisions of consumer, which is also an essential part of consumer's vehicle decisions. Rust(1987) formulate a regenerative optimal stopping model of bus engine replacement through a solution to a stochastic dynamic programming problem. The paper proposes a "nested fixed point" algorithm for estimating dynamic programming models of discrete choice. Melnikov (2001) analyzes the dynamics of consumer choice for discrete choice differentiated products markets with durable goods using data on computer printers and a logit utility specification. But heterogeneity of consumer are only captured by a i.i.d random term and consumers purchase only once in their lifetime.

Recent developments have allowed economists to address the timing of consumer purchase, as in Gowrisankaran and Rysman (2009). This paper estimates a dynamic model of consumer preferences for new durable goods with persistent heterogeneous consumer tastes, rational expectations about future products and repeat purchases over time using data from digital camcorder market. They predict market shares of each product in each period in an industry where prices drop very quickly and product qualities improves significantly over years so that repeated purchases are likely.

In this paper, I specify and estimate a dynamic discrete choice model of consumer demand for automobiles. Heterogeneous consumers decide whether to keep or scrap a car, whether to purchase a new car and which car to own from a set of new car models in the market conditional on purchase. By taking the dynamic elements of demand into consideration, I am able to capture the dynamic nature of a forward-looking consumer's decision, with rational expectation on the evolution of vehicle attributes and retail gasoline prices. I estimate the model separately for each market (city) using a rich dataset combining vehicle registration and current fleet composition data of several cities between 2003 and 2009.

Contrary to the camcorder industry studied in Gowrisankaran and Rysman (2009), prices of automobiles do not drop as quickly as that for digital camcorders. Their characteristics do not improve as fast as camcorders neither. Since estimation in this paper makes use of a seven-year sample of new and used vehicle registration data, it is reasonable to assume that repeated purchase are not going to be frequent. Instead, my model is built based on a similar framework but distinguished from Gowrisankaran and Rysman (2009) by taking into consideration of consumer's dynamic scrappage decisions due to vehicle depreciation and gasoline price dynamics. In addition to the market shares of new vehicles in each year of the sample, as predicted by the model of Gowrisankaran and Rysman (2009), my model also predicts the survival probabilities of each vehicle model-vintage for each year. Therefore, parameters of my model are estimated by matching both set of these predicted shares with the corresponding empirical moments over time.

The parameter estimates from above models are then used to evaluate substantial fuel tax increases that have never been implemented before because they could be considered controversial and/or politically risky. In the United Sates, gasoline taxes vary slightly across states, although the mean total taxes only amount to 47.7 cents per gallon (including federal, state and local tax). Among all industrial countries, the United States has the lowest gasoline taxes, while on the contrary, Germany's tax of $4.86 per gallon is the highest. In addition, there are few changes of federal gas taxes ever since it is first established in 1933. The tax rate has reached the current level of 18.4 cents per gallon through a series of incremental increases and remained unchanged since 1993.

Figure 1 illustrates how average fuel efficiency of passenger cars and light

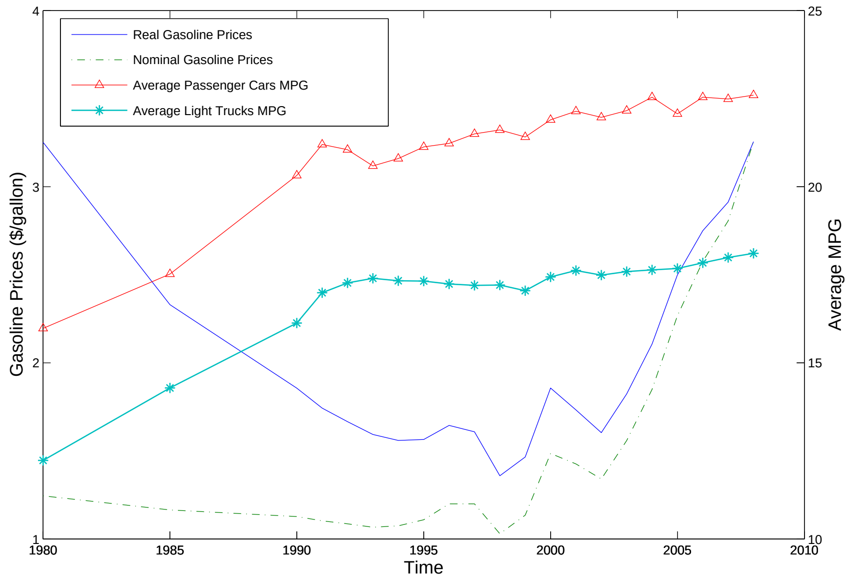

Figure 1: Gasoline Prices and Average Fuel Efficiency in the US, 1980-2008

trucks on road (measured by MPG) evolves in the United States, from 1980 to 2008, along with nominal and real gasoline prices changes. Average MPG for both passenger cars and light trucks both increase from 1980-1990 even when the real gasoline prices is falling during that period. However, in spite of the increased share of sport utility vehicles and light trucks as a percentage of new passenger vehicle sales, average fuel economy is virtually unchanged as gasoline price keep going down between 1990 and 2000. It finally starts to climb up slightly as consumers face the increasing gasoline prices after 2000. One might wonder what will happen to the average fuel efficiency if we could keep a high tax thus a high gasoline price today. With the updating automobile fleets on the market and the changing consumer preferences over the year, it is difficult to study the effects by a reduced form study of historical data. Therefore, a dynamic structural model of consumer choices would be crucial to correctly evaluate policies aimed at increasing fuel efficiency.

Several studies have examined the impact of gasoline taxes on consumer's vehicle choices. Following Dubin and McFadden (1984), Goldberg (1998) and West (2004) studied the joint determination of vehicle choice and gasoline consumption. Bento et al (2008) examined the impacts of increased U.S. gasoline taxes with a model that links the markets for new, used and scrapped vehicles. Li, Haefen and Timmins (2008) examined the effects of gasoline prices on the automobile fleet's composition and found that high gasoline prices shift new purchase towards more fuel-efficiency vehicles and speeding scrappage of less-fuel-efficient used vehicles. Linn and Klier (2007) estimate the effect of a gasoline tax on fuel efficiency of new vehicle purchase, using high frequency sales data. Other studies focus on the impact of policies on new car production and the associated fuel efficiency economy. Goldberg (1998) and Kleit (2004) analyze tighter CAFE standards, while Austin and Dinan (2005) examine CAFE standards and a gasoline tax increase.

However, none of these papers take the dynamic nature of consumer's choice into consideration when they estimated the model and evaluated policy influences. Since different policies have distinct long-run and short run effects, considering a dynamic model is necessary to capture those effects when assessing and comparing policies aimed at improving overall market fuel efficiency.

Compared to the prior works, this paper contributes to the literature by presenting a new and efficiency way to address these issues. Comparisons between my preliminary findings from dynamic demand estimation and results from a static model indicate that the effects of gasoline prices on consumer's vehicle choices are underestimated in a static model. The parameter estimates are then used to evaluate substantial fuel tax increases: the impact of the increase in fuel tax changes over time as the fleet to be replaced is increasingly more efficient as old clunkers get scrapped first. My preliminary results suggest that doubling the current tax rate would result in a decreasing trend of the increase of a city's fleet fuel efficiency after a mild initial impact: an immediate increase of 0.29 MPG, raising up to 1.01 MPG fades out to 0.34 MPG after seven years. Alternatively, a variable tax policy aimed at keeping the price of gasoline stable at $4 per gallon will increase fuel efficiency dramatically to 1.86 MPG in the first several years, remaining mostly stable thereafter, with an increased fuel efficiency of still 1.65 MPG after seven years.

The rest of this paper is organized as following. Section 2 discusses a dynamic model of consumer choices and estimation strategies. Section 3 provides description of data we used in this estimation. Section 4 presents the estimation results from the model and the effects of different tax increase policies based on model simulations. Section 5 concludes.

2 Model And Inference

2.1 Basic Model

Suppose there is a continuum of heterogeneous potential consumers indexed by i in the market. Consumers have infinite horizons and maximize their expected lifetime utility with a common discount factor β.

At the beginning of period t, consumer i may or may not own a car. If he does not have a car, then his decision is whether or not to buy a new car. If consumer i decide to buy a new car at time t, he chooses one among J_t products (Honda Civic, Ford Focus, and so on) in period t. If he owns a car k at time t, he then decide whether to keep the car or scrap the car. If he scraps the car, he can choose to buy a new one among J_t products in period t or choose not to purchase at the current period (e.g. use public transportation instead). In either case, he faces a similar problem at time $t+1$. In this analysis, consumer's decisions of car purchase and replacement mainly depend on current and expected future gasoline prices, which are major components of operation costs. In addition, consumers need to decide whether to replace the vehicle in the current period or later, after comparing the improved features of new models with the depreciation and increasing maintenance cost of the currently owned automobile. Since I do not have vehicle resale data, I assume that there is no resale market.

The indirect utility of consumer i from purchasing product j at time t is:

$$u_{ijt} = \alpha_i^x x_{jt} + \xi_{jt} - \alpha_i^p p_{jt} - \alpha_i^g (\frac{p_t^g}{MPG_{jt}}) + \epsilon_{ijt} \tag{1}$$

Here x_{jt} is the observed product characteristics of vehicle model j at time t, such as horsepower, vehicle size, weight, and so on. ξ_{jt} is the product characteristics of product j at time t that cannot be observed by econometricians and p_{jt} is the price of product j at time t. p_t^g is the retail gasoline price at time t, MPG_{jt} is mileage per gallon of vehicle j at time t. Thus $\frac{p_t^g}{MPG_{jt}}$ is operating costs of owning a car, which is measured by driving costs per mile. ϵ_{ijt} is mean-zero stochastic term with i.i.d. Type I extreme value distribution. Finally, the individual-specific random coefficients $(\alpha_i^x, \alpha_i^p, \alpha_i^g)$ are supposed to be constant overtime and normally distributed:

$$\begin{pmatrix} \alpha_i^x \\ \alpha_i^p \\ \alpha_i^g \end{pmatrix} = \begin{pmatrix} \alpha^x \\ \alpha^p \\ \alpha^g \end{pmatrix} + \Sigma v_i, \tag{2}$$

where $(\alpha^x,\ \alpha^p,\ \alpha^g)$ are mean coefficients and $v_i \sim P_v(v)$ is unobserved consumer preferences.

Then the gross flow utility that each consumer obtains based on his purchase or the car k he already owns at period t is:

$$\begin{cases} \delta_{ikt}^f = \alpha_i^x x_{kt} - \alpha_i^g (\frac{p_t^g}{MPG_{kt}}) - \alpha_i^p dep_{kt} + \xi_{kt} & \text{if}\, k \neq 0 \\ \delta_{ikt}^f = 0 & \text{if}\, k = 0 \end{cases} \tag{3}$$

Here, dep_{kt} is the depreciation costs of owning vehicle k at time t and dep_{kt} is assumed to be zero if it is a new car purchase. I will discuss the depreciation cost later in this section.

Then the utility for consumer i who owns vehicle k at time t could be written as following:

$$\tilde{u}_{ikt} = \delta^f_{ikt} + \epsilon_{ikt} \tag{4}$$

I also define the population mean flow utility as:

$$\bar{\delta}^f_{ikt} = \alpha^x x_{kt} - \alpha^g(\frac{p^g_t}{MPG_{kt}}) - \alpha^p dep_{kt} + \xi_{kt} \tag{5}$$

A consumer who does not own a car at time t has a net flow utility of

$$u_{i0t} = \delta^f_{i0t} + \epsilon_{i0t} \tag{6}$$

where δ^f_{i0t} is the flow utility from the outside good, such as walking to work or using public transportations. Since the mean utility from outside goods is normalized to zero in this model, I assume δ^f_{i0t} equals to zero for those individuals.

Before evaluating consumer's choice decision at time t, I need to formulate consumer's expectations of prices and qualities thus the utility he would obtain from future products, as well as expectations of future gasoline prices at time t. I assume at time t, consumer i has no information about future values of the idiosyncratic unobservable shocks ϵ. Also, although consumer i is uncertain about future values of product characteristics and gasoline prices, he has rational expectations of their evolutions over time.

Let Ω_t denote all information about current and future product attributes available to consumer i at time t (e.g. x_{jt}, p_{jt} and ξ_{jt} $\forall j, t$) and let $\epsilon_{it} \equiv (\epsilon_{i0t}, ..., \epsilon_{iJt})$ be consumer i's idiosyncratic utility components at time t. Then I can define that consumer i at time t makes scrappage or purchase decisions based on the state space $S = (\epsilon_{it}, \delta^f_{ikt}, \Omega_t, p^g_t,)$, where δ^f_{ikt} is consumer's gross utility flow from current endowment of vehicles holding k at time t, $k = 0$ if he does not has a car in current period and p^g_t is gasoline price at time

t. Assume Ω_t, p_t^g and δ_{ikt}^fevolves according to some homogeneous first-order Markov process: $P_1(\Omega_{t+1}|\Omega_t)$, $P_2(p_{t+1}^g|p_t^g)$ and $P_3(\delta_{ik,t+1}^f|\delta_{ikt}^f)$.

2.2 Consumer's Dynamic Optimization Problem

In each period, the consumer is uncertain about gasoline prices, future product attributes and vehicle depreciation, but possess rational expectation of their evolutions. Consumer i's decision is to decide whether to keep his existing vehicle (if any) or to purchase one of the new products. Let $V_i(\epsilon_{it}, \delta_{ikt}^f, \Omega_t, p_t^g)$ denote the value function, I can now define the Bellman equations for consumer i.

If consumer i does not own a car at time t ($k = 0$):

$$V_i(\epsilon_{it}, \delta_{i0t}^f, \Omega_t, p_t^g) = \max \begin{cases} u_{i0t} + \beta E[V_i(\epsilon_{it+1}, \delta_{i0,t+1}^f, \Omega_{t+1}, p_{t+1}^g)|\Omega_t, p_t^g], \\ \max\limits_{j=1,\ldots,J_t} u_{ijt} + \beta E[V_i(\epsilon_{it+1}, \delta_{ij,t+1}^f, \Omega_{t+1}, p_{t+1}^g)|\Omega_t, p_t^g] \end{cases} \tag{7}$$

If consumer i owns a car at time t ($k \neq 0$):

$$V_i(\epsilon_{it}, \delta_{ikt}^f, \Omega_t, p_t^g) = \max \begin{cases} \tilde{u}_{ikt} + \beta E[V_i(\epsilon_{it+1}, \delta_{ik,t+1}^f, \Omega_{t+1}, p_{t+1}^g)|\Omega_t, p_t^g], \\ \max\limits_{j=1,\ldots,J_t} u_{ijt} + \beta E[V_i(\epsilon_{it+1}, \delta_{ij,t+1}^f, \Omega_{t+1}, p_{t+1}^g)|\Omega_t, p_t^g], \\ u_{i0t} + \beta E[V_i(\epsilon_{it+1}, \delta_{i0,t+1}^f, \Omega_{t+1}, p_{t+1}^g)|\Omega_t, p_t^g] \end{cases} \tag{8}$$

The main issue in solving the consumer's dynamic programming problem here is the "curse of dimensionality" of the state space. Following the existing literature, I make some assumptions to simplify this problem. Following Rust (1987), I define

$$EV_i(\delta_{ikt}^f, \Omega_t, p_t^g) = \int_{\epsilon_{it}} V_i(\epsilon_{it}, \delta_{ikt}^f, \Omega_t, p_t^g) dP_\epsilon \tag{9}$$

By integrating over realization of ϵ_{it}, expectation of value function EV_i is not a function of ϵ_{it}, and the choice probabilities will not require integration over unknown function EV_i. Since ϵ_{ijt} is assumed to be i.i.d. Type I extreme value distributed, the conditional independence assumption from Rust (1987) is satisfied. Now EV_i is a fixed point of a separate contraction mapping on the reduced state space $S' = (\delta^f_{ikt}, \Omega_t, p^g_t)$

Since Ω in the state space S contains all information about current and future product attributes available to consumer at time t, the large dimensionality makes it difficult to compute the Bellman equations in (7) and (8). To solve the dimensionality problem, I further make some simplifications and introduce the logit inclusive value. For $j = 1, ..., J$, define

$$\delta_{ijt}(\Omega_t, p^g_t) = \delta^f_{ijt} - \alpha^p_i p_{jt} + \beta E[EV_i(\delta^f_{ij,t+1}, \Omega_{t+1}, p^g_{t+1}|\Omega_t, p^g_t)] \qquad (10)$$

Therefore, δ_{ijt} is the expected discounted utility for consumer i purchasing product j at time t. Then the logit inclusive value for consumer i at time t is

$$\delta_{it} = \ln\left(\sum_{j=1,...,J_t} \exp(\delta_{ijt}(\Omega_t, p^g_t))\right) \qquad (11)$$

The logit inclusive value simplifies the consumer's utility of choosing j from the entire set of J_t to receiving product with mean utility δ_{it} and a random draw from extreme value distribution.

$$EV_i(\delta^f_{ikt}, \Omega_t, p^g_t) = EV_i(\delta^f_{ikt}, \delta_{it}, E[\delta_{i,t+1}, \delta_{it+2}, ...|\Omega_t, p^g_t], p^g_t) \qquad (12)$$

Now consumer's dynamic decision in each period can be interpreted as following. Based on his current flow utility and expectation of future gasoline prices and product attributes, he first decide whether to replace the car (if any) this period by simply comparing the logit inclusive value to the outside option (not buying a car or not replacing the current car). Then he can make the optimal choice of a new vehicle among all available products if he decides to buy.

Further, I assume that,

$$\text{If } \delta_{it}(\Omega_t, p_t^g) = \delta_{it}(\Omega_t', p_t^g), \qquad P(\delta_{it+1}|\Omega_t, p_t^g) = P(\delta_{it+1}|\Omega_t', p_t^g) \tag{13}$$

This assumption implies that, given the same gasoline prices, if at period t the logit inclusive value δ_{it} is the same for two states, then the evolution for future logit inclusive value will be the same. Then the evolution of logit inclusive value can be assumed to follow the stochastic process:

$$P(\delta_{it+1}|\delta_{it}) \tag{14}$$

With this assumption, the evolution of the logit inclusive value δ_{it} only depends on its own last period value. Similarly, the evolution of gasoline prices is assumed to depends only on its own last period value and follow the following stochastic process:

$$P(p_{t+1}^g|p_t^g) \tag{15}$$

Depreciation is usually the greatest expense incurred by drivers during their ownership period. As the automobile ages, the required maintenance costs and probability of failure both increase, thus the consumer tends to receive less utility flow from owning vehicle k in period $t+1$ than in period t due to depreciation. To capture this, I form consumer's expectation on the evolution of expected values of keeping the currently owned vehicle, where the depreciation cost is expressed through its declining resale values as a percentage of its original price. Another way to capture depreciation is simply thorough the vehicle age. Since different vehicle models have significantly different abilities of retaining their values, I use resale values for better preciseness. For example, a Toyota Camry Sedan can retain 65% of its retail price for the second year and 38% for the fifth year, way above Kia Optimal

LX Sedan, with 36% and 18%.[2] Let $Dep = p_{kt} - \beta E[p_{k,t+1}|\delta^f_{ikt}, p^g_{t+1}]$. This is the difference between period t's resale value and expected period resale value in $t + 1$, which depends on vehicle k's own characteristics and retail gasoline prices. I approximate this value as a fraction of vehicle's original price, i.e., $Dep_{kt} = \lambda_{kt} P^{origin}_k$. Assume consumer's expected utility δ^f_{ikt} from owning vehicle k evolves according to the following stochastic process:

$$P(\delta^f_{ik,t+1}|\delta^f_{ikt}) \tag{16}$$

In order to solve the dynamic decision problem, I need to further specify consumer's expectations. The process are modeled independently and I assume a simple and computable linear specification for each of them:

$$\delta_{i,t+1} = \gamma_{1i} + \gamma_{2i}\delta_{it} + u_{it} \tag{17}$$
$$\delta^f_{ik,t+1} = \mu_{1i} + \mu_{2i}\delta^f_{ikt} + \upsilon_{it} \tag{18}$$
$$p^g_{t+1} = \kappa_{1i} + \kappa_{2i}p^g_t + \eta_{it} \tag{19}$$

where γ, μ, κ are incidental parameters and $u_{it}, \upsilon_{it}, \eta_{it}$ are normally distributed with mean 0. These equations can be estimated through linear regressions.

Using the simplifying assumptions I made above, I am now able to reduce the state space from many dimensions to three dimensions:

$$EV_i(\delta^f_{ikt}, \delta_{it}, E[\delta_{i,t+1}, \delta_{i,t+2}, ...|\Omega_t, p^g_t], p^g_t) = EV_i(\delta^f_{ikt}, \delta_{it}, p^g_t) \tag{20}$$

where δ^f_{ikt} is the flow utility from current endowment k at time t, δ_{it} is logit inclusive value (mean utility level) of all products available at time t and p^g_t is the gasoline price at time t.

Now I can write the expectation of the Bellman equation as:

[2]Resale Value from Kelly Blue Book

If consumer i does not own a car at time t ($k = 0$):

$$EV_i(\delta^f_{i0t}, \delta_{it}, p^g_t) = \ln\left(\exp(\delta_{it}) + \exp\left(\delta^f_{i0t} + \beta E\left[EV_i(\delta^f_{i0,t+1}, \delta_{i,t+1}, p^g_{t+1})|\delta_{it}, p^g_t\right]\right)\right) \tag{21}$$

If consumer i owns a car at time t ($k \neq 0$):

$$\begin{aligned} EV_i(\delta^f_{ikt}, \delta_{it}, p^g_t) &= \ln(\exp\left(\delta^f_{ikt} + \beta E\left[EV_i(\delta^f_{ik,t+1}, \delta_{i,t+1}, p^g_{t+1})|\delta_{it}, p^g_t\right]\right) + \exp\left(\delta_{it}\right) \\ &+ \exp\left(\delta^f_{i0t} + \beta E\left[EV_i(\delta^f_{i0,t+1}, \delta_{i,t+1}, p^g_{t+1})|\delta_{it}, p^g_t\right]\right)) \end{aligned} \tag{22}$$

The aggregate demand for each vehicle can now be characterized in a straightforward manner. With the standard extreme value assumption, for a consumer i with vehicle k ($k = 0$ or $k \neq 0$), the probability of purchasing a certain product j conditional on purchase is:

$$Pr_{ijt} = \frac{\exp(\delta_{ijt})}{\exp(EV_i(\delta^f_{ijt}, \delta_{it}, p^g_t))} \tag{23}$$

For a consumer i who owns a car ($k \neq 0$) at time t, the probability that consumer i keeps the current vehicle is :

$$\widetilde{Pr}_{ikt} = \frac{\exp\left(\delta^f_{ikt} + \beta E\left[EV_i(\delta^f_{ik,t+1}, \delta_{i,t+1}, p^g_{t+1})|\delta_{it}, p^g_t\right]\right)}{\exp(EV_i(\delta^f_{ikt}, \delta_{it}, p^g_t))}$$

Now the market share of each vehicle model j purchased at period t and the market share for each vehicle holdings could be calculated by integrating the probabilities Pr_{ijt} and $\widetilde{Pr}_{ikt}$ over consumer preferences:

$$s^N_{jt} = \int_{v_i} \sum_{k \in J_{t-1} \cup 0} Pr_{ijt}\, \widetilde{s}_{ik,t-1}\, dP_v(v) \tag{24}$$

$$\widetilde{s}_{kt} = \int_{v_i} \widetilde{Pr}_{ikt}\, \widetilde{s}_{ik,t-1}\, dP_v(v) \tag{25}$$

Now I have recovered the explicit expressions of market shares for new car sales s_{jt}^N and existing used car holdings $\widetilde{s}_{kt}$, which could be observed in our vehicle registration data.

2.3 Inference

The estimation strategies are built on Gowrisankaran and Rysman (2009): combining BLP and Rust (1987)'s nested fixed point algorithm to estimate parameters of the model. The outer loop is a non-linear search over parameters (α, Σ) of the model; the middle loop is a fixed point calculation of the population mean flow utilities $\bar{\delta}_{ikt}^f$ and the inner loop is calculation of predicted market shares, based on consumer's dynamic optimization decisions. I now briefly describe some details of the three levels of optimization.

Instead of trying to estimate the discount factor β in the dynamic model, I set $\beta = 0.9$.[3]

The inner loop computes the predicted market share as a function of $\bar{\delta}_{kt}^f$ for and necessary parameters by solving the consumer dynamic programming problem for a number of simulated consumers and then integrating across consumer types. Following literature, the predicted market shares were obtained through simulation since there's no closed form solution for (24) and (25).

The middle loop, I recovered the population mean flow utility $\bar{\delta}_{kt}^f$ using the contraction mapping developed by BLP. In particular, I use an iterative routine that update the mean flow utility until convergence as follows:

$$\bar{\delta}_{kt}^{f,n} = \bar{\delta}_{kt}^{f,o} + \psi(\ln(\widetilde{s}_{kt}) - \ln(\hat{\widetilde{s}}_{kt}(\bar{\delta}_{kt}^{f,o}, \alpha, \Sigma))) \tag{26}$$

where $\hat{\widetilde{s}}_{kt}(\bar{\delta}_{kt}^{f,o}, \alpha, \Sigma)$ is the predicted market share calculated from inner loop, $\widetilde{s}_{kt}$ is the actual market share from data, $\bar{\delta}_{kt}^{f,n}$ is the current and $\bar{\delta}_{kt}^{f,o}$ is the

[3]Since the computing time may varies substantially with different value of β, the actual value of β used in the estimation is subject to change.

previous iteration flow utility value and ψ is a tuning parameter that usually set to $1-\beta$. Conditional on the vector of parameters, I iteratively updated the logit inclusive value, the value functions, the Markov process until fully convergence.

In the outer loop, I specify a GMM criterion function:

$$G(\alpha, \Sigma) = Z'\xi(\alpha, \Sigma) \tag{27}$$

where $\xi(\alpha, \Sigma) = \bar{\delta}^f_{im\omega t} - \alpha^x x_{\omega t} + \alpha^g (\frac{p^g_{mt}}{MPG_{\omega t}}) + \alpha^p dep_{\omega t}$ is the unobserved product characteristics from (5) and Z is a matrix of exogenous variables, which I will describe in details later. Then the estimated parameters (α, Σ) should solve:

$$\min_{\alpha, \Sigma} G(\alpha, \Sigma)' W G(\alpha, \Sigma) \tag{28}$$

I solve this minimization problem by a non-linear search over (α, Σ). In addition, I obtain consistent estimates of (α, Σ) through a two-stage estimation. In the first stage, assuming homoscedastic errors, I let $W_1 = Z'Z$ and get estimates for (α, Σ). Then I use the first stage estimates to approximate the optimal weight matrix and perform the second estimation for parameters.

The key identifying assumption in this estimation is the population moment condition $E[Z'\xi(\alpha, \Sigma)] = 0$, which requires a set of exogenous instrumental variables. Following BLP, I allow vehicle price to be endogenous to the unobservable ξ_{jt}, and assume that product characteristics are exogenous. I use all product characteristics, the mean product characteristics of vehicle model from the same producer at the same period, the mean product characteristics for all models at the same period. These instruments are all common in the literature.

3 Data

The empirical analysis of this paper relies on several types of dataset combined together: the annual vehicle registration data for Houston and San Francisco from R.L.Polk & Company; automobile characteristics from Ward's Automotive Year Book; retail gasoline prices of the two cities from Energy Information Administration, and vehicle fuel economy efficiency data from Environmental Protection Agency. By merging all those dataset together, I have obtained a very rich dataset which allows me to identify the model and to do policy comparison simulations.

The main dataset I used contains vehicle registration data for Houston and San Francisco. The data was purchased from R.L.Polk & Company and it include registration records for both new and used vehicles from 2003 to 2009. The new vehicle registrations are collected at model level by Model year/Make/Model in each city (e.g. how many 2003 Honda Civic were purchased in Houston in 2003) thus I could keep track of new car sales each year. The used car registration data for all vehicle stocks at model level in each city are also included in the data thus I could observe the evolution of the fleet composition at model level over the seven years. Since vehicle registration is required once every year, all registration data above are in year level.

I also supplement the registration data with vehicle characteristics data. This information is from the annual Ward's Automotive Yearbooks (2003-2009), which provide most of the vehicle characteristics used in this analysis by make, model and year. The data include wheelbase, length, width, height, curb weight, engine size, horsepower, retail prices, and so on. Price data is based on list prices, which is subject to some measurement errors given that most transactions in the US car market are negotiable. In this estimation, all prices are in 2003 dollars. (I use the Consumer Price Index to deflate.)

The vehicle fuel efficiency data are from the Environmental Protection Agency (EPA), measured by a weighted average of city(55%) and highway

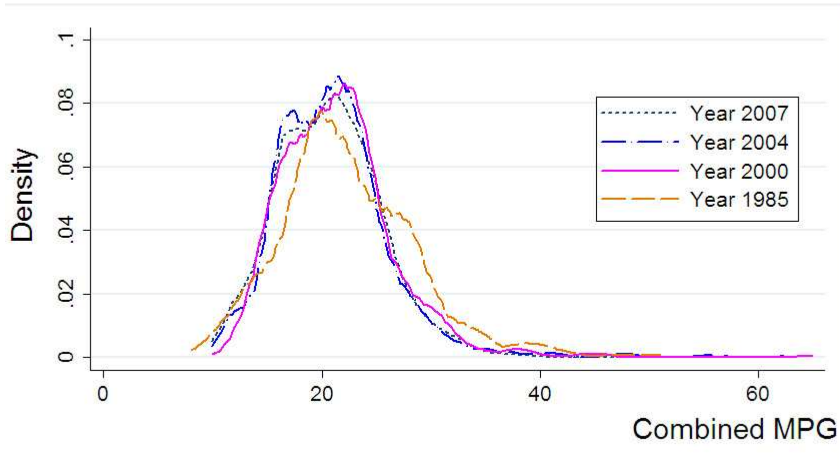

Figure 2: Kernel Density Estimation of Fuel Economy Distribution

(45%) mileage per gallon (MPG).[4] The average MPG for all vehicle models shown in our sample is 21.71, with a standard deviation of 4.93. Figure 2 graphs the kernel density estimates of fuel economy distribution for all vehicle models sold in the U.S. in year 1985, 2000, 2005 and 2007. Surprisingly, the fuel efficiency, which is measured by MPG, was declining from 2000 to 2007 in general since the probability density function was shifting leftward towards lower MPG. This can be largely explained by increasing sales and market expansion of SUVs and light trucks in recent years.

Table 3 provides summary descriptive statistics of variables used in this analysis. On average, horsepower to weight ratio for all vehicle models on the market is 0.13, while the mean size for vehicles, which is measured by length $\times$ width, is 13740. The average MPG is 21.71 for all models with a driving cost of 12 cents per mile. For every one hundred models, 53 of them are passenger cars and 40 of them are SUVs, while only 7 are trucks.

The retail gasoline prices in each city are from Energy Information Administration. There is substantial periodical and regional variation in retail gasoline prices: Houston experienced the lowest annual average price of \$1.8

[4]Mileage per gallon here is computed as: $\text{MPG} = \frac{1}{(0.55/\text{City MPG}+0.45/\text{Hwy MPG})}$)

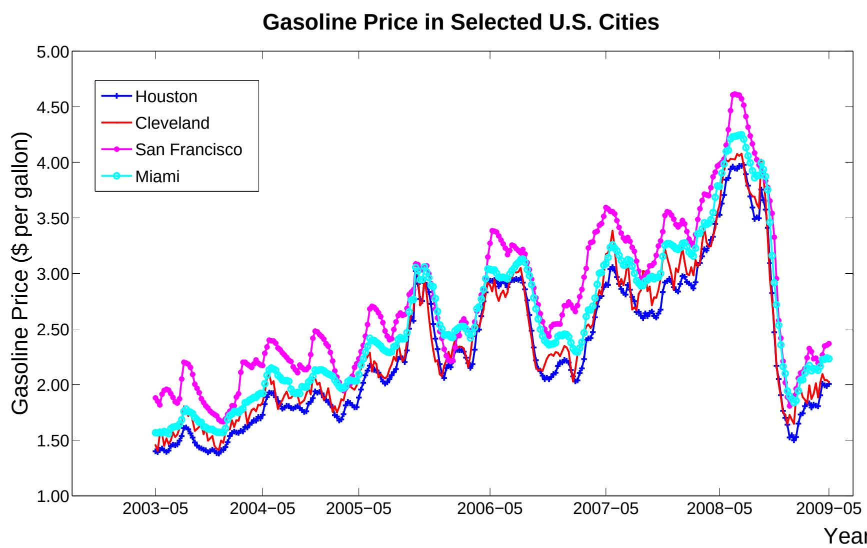

Figure 3: Gasoline Prices in Selected U.S. Cities

per gallon while the highest appeared in San Francisco in 2008, with \$ 3.82 per gallon. Figure 3 gives a clearer illustration by comparing gasoline prices in Houston, San Francisco, Cleveland and Miami during the sample periods, 2003-2009. In general, there is an upward trend for retail gasoline prices across the whole country except for the sharp drop in late 2008 due to the decline of world demand. The price variation across time will help us better identify the model.

Figure 4 plots how average mileage per gallon in Houston moves with gasoline prices from 2003 to 2009, on a yearly basis. The weighted average MPG for new car sales soars as the gasoline prices increase since 2003. However, it started to drop long before the gasoline price peaks in 2008. For car stocks in Houston, the fuel efficiency kept decreasing due to the prevailing consumer preference for SUV and trucks. But the rate of decreasing drops as gasoline prices increase over year. These findings provide an illustrative demonstration on how gasoline price affect a city's average MPG over year.

Combining registration information of each city with vehicle characteris-

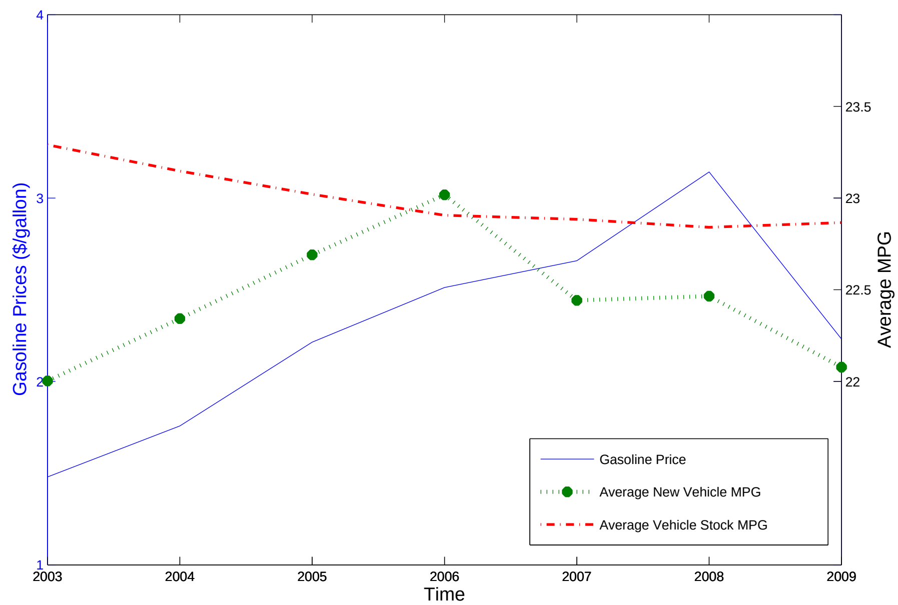

Figure 4: Gasoline Prices and Average MPG in Houston, 2003-2009

Variable	Mean	Std. Err
HP	222.35	76.60
Weight	3740.00	808.05
HP/Weight	0.13	2.01
SIZE (Length $\times$ Width$\times 10^{-3}$)	13.74	1.64
MPG	21.71	4.93
Fuel Cost ($)	0.12	0.04
Passenger Car	0.53	0.50
SUV	0.40	0.49
Truck	0.07	0.26
Price ($)	36211.24	40713.48

Table 1: Statistics of Vehicle Characteristic, 2003-2009

tics data, I can now recover the weighted fuel efficiency and weighted fleet composition in each city across years. Table 3 shows a sample characteristics for Houston and San Francisco for comparison. For fleet composition in two cities, the weighted average fuel efficiency of new car sales is 22.45 miles per gallon in Houston, which is much lower than that of 25.79 miles per gallon in San Francisco. Here is an important difference between the two markets over years, which could be explained by the following fleet composition comparison. For new car sales, 61% of all vehicles sold in San Francisco are passenger cars, which are usually more fuel efficient. However, only 45% of new vehicle purchase in Houston are passenger cars. Specifically, consumers in Houston show an remarkable passion of trucks: over 20% of new car sales in Houston is trucks, while only 7% in San Francisco. The fleet composition of vehicle stocks is also quite similar to new car sales in two cities, as demonstrated in the Table.

In order to capture the depreciation costs of owning vehicles, I use resale values of vehicles. This information was collected from Resale Value of Kelly Blue Book. Resale value is a projection based on the current market, historical trends, market conditions for the vehicle, competition in the segment and expectations of the future economy. It is typically represented as a percentage of a vehicle's original MSRP and is used for estimating the vehicle's value when it is sold or traded in. Table 3 gives a sample comparison of some vehicle models.

4 Estimation Results and Discussions

In this section, I first discuss the estimation results from previous dynamic demand model in section 4.1. To complete the picture of how gasoline prices affect the fleet composition and thus the fuel efficiency in each city, I further conduct simulations of gasoline tax increases in section 4.2.

Variable		Houston, TX	San Francisco, CA
	Average Gasoline Price ($)	2.25	2.67
New Vehicle			
	Average Fuel Efficiency (MPG)	22.45	25.79
	Percentage of Passenger Car	0.45	0.61
	Percentage of SUV	0.34	0.31
	Percentage of Trucks	0.21	0.07
Vehicle Stocks			
	Average Fuel Efficiency (MPG)	22.99	25.15
	Percentage of Passenger Car	0.56	0.73
	Percentage of SUV	0.24	0.20
	Percentage of Trucks	0.20	0.06
	Average Fleet Age (Year)	8.63	9.71

Table 2: Sample Demographic Statistics of Houston and San Francisco, 2003-2009

Model	Make	Year 1	Year 2	Year 3	Year 4	Year 5
Audi	A6	1	0.41	0.34	0.29	0.24
BMW	X5	1	0.69	0.59	0.49	0.41
Chrysler	PT Cruiser	1	0.33	0.28	0.24	0.2
Ford	Focus	1	0.45	0.36	0.28	0.24
Honda	Civic	1	0.58	0.51	0.47	0.43
Kia	Optima	1	0.36	0.27	0.21	0.18
Nissan	Altima	1	0.6	0.51	0.43	0.37
Pontiac	G6	1	0.39	0.31	0.25	0.21
Toyota	Corolla	1	0.61	0.54	0.48	0.44
VW	Passat	1	0.42	0.35	0.3	0.26
Volvo	S60	1	0.46	0.36	0.29	0.24

Table 3: Average Resale Value of Selected Vehicle Models

4.1 Results

Estimation results of the dynamic demand model are described in this section. The first two columns of Table 4 reports parameter estimates for the dynamic demand specification using Houston data. The top panel of Table 4 presents the estimated parameters associated with the characteristics of the vehicle in consumer's utility specification. In this model, I use three random coefficients, vehicle price, fuel cost, and constant term. The estimated standard deviation for random coefficients are listed in the bottom panel. The price variable is in log term. As expected, price contributes negatively to consumer's utility, with a base coefficient of -0.6445 and a standard deviation of the random coefficient of 0.0328. The constant term has a base coefficient of -2.0091, suggesting that a person with mean tastes would obtain a negative gross flow utility from a vehicle with all other characteristics zero (relative to the outside option). In addition, the significant standard deviation for the constant term indicates the heterogeneity of consumer's utility from a vehicle of zero characteristics, while still negative.

The third random coefficient, fuel cost, is of special interest to us in this paper. Fuel cost, measured by dollar per mile, is defined by the real price of unleaded gasoline prices divided by the fuel efficiency of the vehicle model (in MPG). It is often viewed as the unit price of driving and in this case I use this as a proxy for operating costs. The base coefficient for fuel cost is negative and significant, which is consistent with our expectation: an increase in operating cost per mile for any vehicle can be expected to reduce consumer's utility from owning the vehicle. The standard deviation of fuel cost is precisely estimated at 2.6510, implying a large variance in distribution of of consumer's tastes for fuel cost, thus gasoline prices.

I also include four variables to express vehicle characteristics, including two dummy variables that indicate vehicle's type (passenger car, SUV or light trucks). All of the characteristics are significant except for dummy variable SUV. The coefficients for characteristics, in general, are much smaller than random coefficients in terms of absolute values. Positive and significant coefficients for horsepower to weight ratio and vehicle size show that consumers in Houston would prefer larger cars with bigger horsepower. The coefficient for dummy variable Passenger Car supports a similar argument: the negative sign indicate that owning a passenger car would contribute negatively to consumer's utility in general.

The last two columns of Table 4 present estimation parameters from a static model for comparison. The static model follows BLP and estimates a random coefficient discrete choice model. Under the static setting, consumer choose between different types of new cars and they face no dynamic decisions from gasoline price and product feature evolutions. The coefficient for fuel cost in the static model is -5.3372, which is much smaller than that in the dynamic model. This result coincides with our previous argument: in a static model without consumer's expectation for future gasoline prices changes, we

Variable		Dynamic Model Estimates	Dynamic Model Std.Err	Static Model Estimates	Static Model Std.Err
	Constant	-2.0091	0.2506	1.9191	0.5723
α_i^g	Fuel Cost (Dollar per Mile)	-10.0105	4.8899	-5.3372	0.8768
α_i^p	LN Price	-0.6445	0.1197	-0.9660	0.1354
α^x	HP/Weight	0.0308	0.0033	0.7728	0.4671
	SIZE (Length $\times$ Width $\times 10^{-3}$)	0.1115	0.0362	0.0110	0.0023
	Passenger Car	-0.7232	0.3264	0.5931	0.1615
	SUV	0.0613	0.2499	0.8631	0.1551
Standard Deviation of Random Coefficients ($\Sigma^{1/2}$)					
	Constant	0.0271	0.0086	0.0003	3.2436
	Fuel Cost	2.6510	0.6050	0.7349	0.908
	LN Price	0.0328	0.0098	0.0288	0.1148

Table 4: Dynamic Demand Estimation Results–Houston

may underestimate the effect of gasoline prices on consumer's vehicle choices.

As with any discrete choice model, the coefficients from Table 4 do not give the marginal effects on owning probabilities. I translate the parameters into marginal effects on fuel cost changes for different types of cars in Table 7. In particular, I compute the average percentage change in probabilities of new car purchase, as well as used car holdings, holding other variables fixed. In column 1, I report the average percentage change for one dollar increase in fuel cost in Houston. For new car purchase, the probabilities of purchasing for passenger cars, SUVs and light trucks all declined. SUV sales receives the biggest impact in Houston and decreases by 5.01% , followed by passenger cars of a 4.96% decline in purchasing probability. However, the sales of light trucks are least influenced by fuel cost increases, indicating that consumer's demand for light trucks in Houston are least elastic. Turning to vehicle holdings, as gasoline prices increase, the survival probability for passenger cars increases by 4.32%, while those for SUVs and light trucks both decrease in Houston.

As the model relies on the simplifying assumption of logit inclusive value for consumer's choice decision, I plot the evolution of logit inclusive value δ_{it} to see how it evolves over time. In general, the logit inclusive value represent the expected value consumers get from all vehicle models on the market and are computed based on the structural parameters estimated previously. Figure 5 plot the 20 percentile, 50 percentile and 90 percentile of logit inclusive value over time. It shows that in general, there is an upward, as well as roughly linear, trend over time, which indicate that consumers' valuation for vehicles is increasing in the sample period.

In addition, I also estimate a similar model for San Francisco. The comparison between the results for two cities with distinctive geographic and demographic characteristics would reveal how gasoline price will impact consumer's choice for vehicle replacement under different circumstances. The estimation results for San Francisco are presented in Table 5. The signs for random coefficients are the same for Houston and San Francisco, suggesting that gasoline prices and vehicle prices contribute negatively to consumers' utilities. Standard deviations for random parameters are all statistically significant, indicating that there is substantial variations in the consumer's taste for vehicle price and operating costs.

To see how consumers in different markets react differently to vehicle attributes, Table 6 compares signs of the estimated parameters for the two cities specifically. Similar to Houston, the higher the horsepower to weight ratio, the greater the utility consumers received from owing the vehicle. On the other hand, it is worthy to notice two distinctive differences of estimated parameters between the two cities: vehicle size and dummy variable for passenger car. The coefficient for vehicle size is negative and significant, while the dummy variable passenger car is precisely estimated to be positive. This result suggest that, in San Francisco, consumers tend to prefer a passen-

Variable	Estimates	Std.Err
Constant	-5.2463	1.3713
Fuel Cost (Dollar per Mile)	-34.5239	15.3594
LN Price	-0.8125	0.1476
HP/Weight	0.0085	0.0192
SIZE (Length $\times$ Width/1000)	-0.0073	0.0029
Passenger Car	0.1773	0.0795
SUV	0.0526	0.0074
Standard Deviation Coefficients ($\Sigma^{1/2}$)		
Constant	0.0033	9.2568
Fuel Cost	0.0055	4.8144
LN Price	0.0051	3.9117

Table 5: Dynamic Demand Estimation Results – San Francisco

ger car with smaller size, which is opposite to consumer's taste in Houston. It somehow reflects the distinctive environment in the two cities, in terms of variation in vehicle composition, city characteristics and gasoline prices. The marginal effects on fuel cost changes in San Francisco are also slightly different from that in Houston. Although the purchasing probabilities of passenger cars, SUVs and light trucks all decrease due to the increase of gasoline prices, the sales of trucks are the one that get the largest impacts, followed by passenger cars and SUVs.

4.2 Policy Simulation and Comparison

The main purpose for this paper is to investigate how gasoline prices affect vehicle fuel efficiency in a city. In the previous section, gasoline price is found to have significant effects on consumer's utility of owning a vehicle, thus a

Variable		Sign of Coefficients	
		Houston	San Francisco
	Constant	-	-
α_i^g	Fuel Cost (Dollar per Mile)	-	-
α_i^p	LN Price	-	-
α^x	HP/Weight	+	+
	SIZE (Length $\times$ Width $\times 10^{-3}$)	+	-
	Passenger Car	-	+
	SUV	+	+

Table 6: Dynamic Demand Estimation Results Comparison: Houston v.s. San Francisco

Change in Probability (%)	Houston	San Francisco
New Car Purchase		
Passenger Car	-4.96	-5.96
SUV	-5.01	-5.89
Truck	-3.66	-6.97
Survival Prob		
Passenger Car	4.32	5.48
SUV	-1.47	-4.39
Truck	-2.65	-6.16

Table 7: Marginal Effect on Fuel Cost Change for Different Vehicle Types

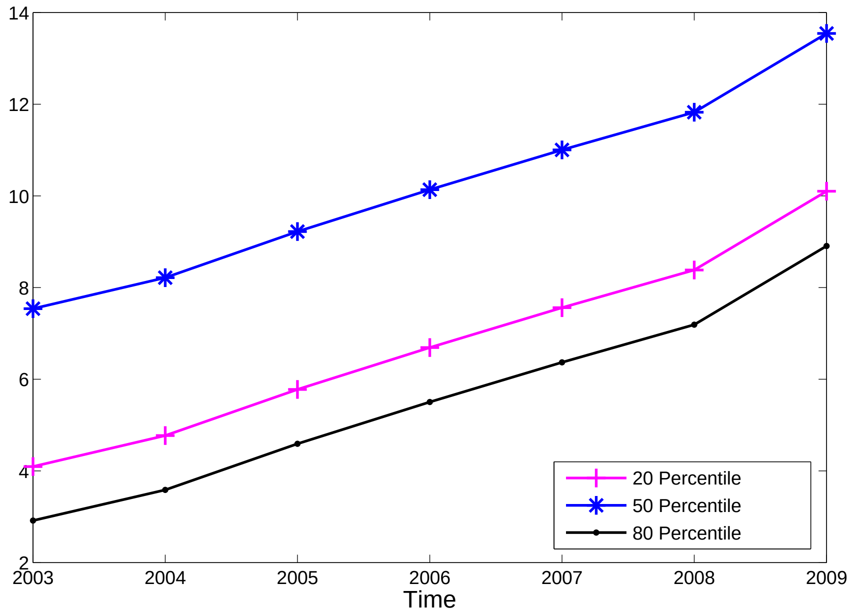

Figure 5: Evolution of Logit Inclusive Value Over Time

indirect impact of the fuel economy efficiency in a city. To see how fleet fuel efficiency response to gasoline price changes, thus the operating costs change, I conduct simulations under two different scenarios.

In particular, I simulate the response of fleet fuel economy under two different gasoline tax policies. The advantage of this dynamic model is that I incorporate the dynamic response of consumers to examine the long run impact on fleet fuel economy of gasoline tax increase. Specifically, in this section, I first simulate an increase in the federal gasoline tax for 50 cents per gallon. Since currently average gasoline tax per gallon is around 47.7 cents, including federal, state and local taxes, a 50 cents increase would be equivalent to doubling current tax rate. Further, I translate the increase of gasoline prices due to raising gasoline tax into an increase in operating costs, i.e., fuel cost per mile for each vehicle model available on the market, and then simulate consumer's responses in new car purchase and vehicle holdings. For example, under current average gasoline price of \$2.58 in Houston, a 50 cents tax increase would raise the operating costs of a vehicle with 30 MPG from \$0.086 per mile to \$0.103 per mile, which is almost 20% increase.

As I mentioned previously, among all industrial countries, U.S. has the lowest gasoline tax, while Germany has the highest of roughly \$4.86 per US gallon. Although a \$4.86 gasoline tax is by no means politically feasible in the U.S., for illustration purpose, I consider a gasoline tax increase that would maintain the gasoline prices at a \$4 level, which was once reached for a very short time during the high gasoline price period in mid 2008 in some cities.

Table 8 presents the effect of gasoline tax increase starting 2003 on average fuel efficiency economy in Houston and San Francisco in the next 7 years, holding vehicle characteristics and market demographic variables constant. Column I and II shows the simulated average fleet fuel efficiency under a \$ 4 gasoline prices, while column III and IV presents the average MPG in two cities if I double current gasoline taxes. To make it more clear, Figure 6 and

7 plot the simulated fleet fuel efficiency to investigate the dynamic response under different assumptions by examining the time path of the average fuel efficiency changes. As a benchmark, the black dotted line plots the original average fuel efficiency in two cities, respectively. In general, after considering the dynamic effects on consumer choices, we observe significantly different on-impact response and long-run effects on average MPG. In addition, under the two alternative gasoline taxes experiments, the time paths of a city 's average MPG evolution is also quite different.

For Houston, in general, there is an increase in average MPG, while the magnitude is relatively small, even under a persistent 4 dollars gasoline prices over the seven years.

In the long run, under a \$4 gasoline price, there is an upward trend for average fuel efficiency starting from 2003, from 22 MPG to 23.65 MPG. Specifically, the average fuel efficiency increase dramatically in the first four years of the policy change. A possible explanation for this would be that new car purchase are affected more by the tax years for old, inefficient cars to get scrapped, or exit the market. This could also be true if our model take into consideration of the used car resale market. Even if a consumer sold a used car to purchase a new efficient one, as long as the used car is still on road, it still be counted into the city's average fuel efficiency. Therefore, we observe a drop after four years and a rebound in fuel efficiency shortly after when more old car scrappage happens. On the other hand, if doubling gasoline taxes in 2003, the average fuel efficiency will increase only in the first three years and start to decline ever since, resulting in a 0.05 MPG increase only after seven years. The distinctive dynamic path under double gasoline tax suggest that if a gasoline tax is not high enough, the impact of a city's fleet fuel efficiency will fade out very quickly.

On the contrary, average fuel efficiency in San Francisco is much more responsive to gasoline price increase under the dynamic setting when consumer expect the price change to be permanent. Unlike the Houston results,

	Keep $4 Gasoline Prices (MPG)		Double Current Gasoline Tax (MPG)	
Year	Houston	San Francisco	Houston	San Francisco
2003	22.39	28.28	22.29	25.72
2004	22.71	29.57	22.15	26.97
2005	23.44	29.41	23.27	27.34
2006	23.86	28.80	23.01	27.53
2007	23.40	29.00	22.61	28.28
2008	23.54	28.47	22.55	27.32
2009	23.65	29.48	22.34	27.09

Table 8: Average Fuel Efficiency (MPG) in Cities Under Different Gasoline Tax Simulation

when gasoline tax was doubled, the dynamic path of fuel efficiency are quite persistent for the first four years, with a series of incremental increase to 2.81 miles per gallon in total, It then start to decline slightly over year, to an increase of 1.37 MPG. Similar to Houston, both time paths experience a down turn after three to four years of the policy change and a rebound one to two years after. When the gasoline price increases to four dollars, the average fuel efficiency in San Francisco, on average, is around 2 miles per gallon higher than that under double tax, except for the draw down period after three years. At the end of the sample period, the average fuel efficiency attains 29.43 miles per gallon, with an increase of 4.76 MPG.

The distinctive differences of consumers' response to gasoline tax increase reflect market heterogeneity among U.S. cities that result from consumer's tastes for vehicle type, market demographic and geographic features. Therefore, in order to attain a more effective change in fuel efficiency in cities, a market-specific tax policies would be preferred.

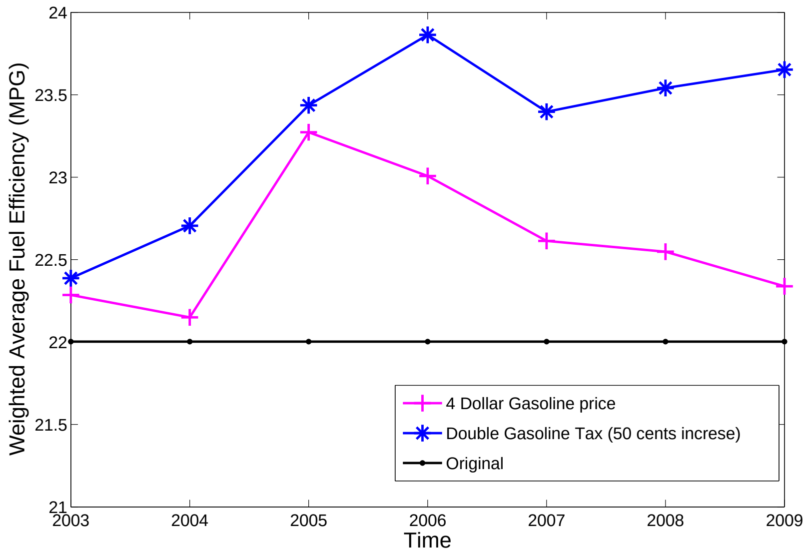

Figure 6: Simulated Average MPG in Houston after Tax Increase, 2003-2009

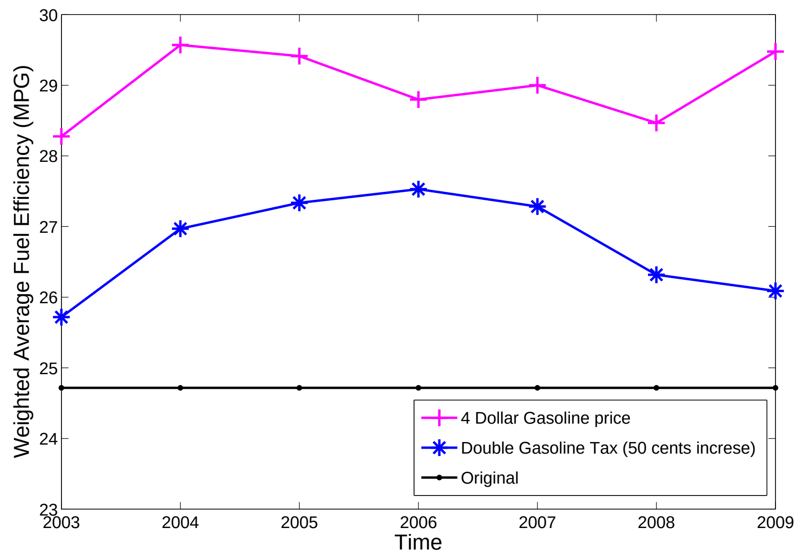

Figure 7: Simulated Average MPG in San Francisco after Tax Increase, 2003-2009

5 Conclusion and Future Work

How much gasoline prices affect consumer's vehicle choices and fuel economy efficiency in a market? To answer the question and further study the true effect of raising gasoline tax, I have estimated a structural dynamic discrete choice model where heterogeneous consumers choose whether to keep or scrap a car, whether to purchase a new car and which car to own from a set of new car models in the market conditional on purchase.

Gasoline price dynamics plays an important role in a consumer's decision making process that cannot be captured in a static model, which leads to underestimating of gasoline price effects. Therefore, a dynamic model of consumer choice would be crucial to correctly evaluate any policy aimed at increasing fuel efficiency. In this paper, I specify and estimate a structural dynamic model of consumer preference for new and used vehicles by exploring a rich dataset combining vehicle registration and current fleet composition data of several cities between 2003 and 2009. My model was built based on a similar framework but distinguished from Gowrisankaran and Rysman (2009) by taking into consideration of consumer's dynamic scrappage decisions due to vehicle depreciation and gasoline price dynamics. Indeed, my model not only predicts the market share of each vehicle model sold in every period but also the survival probability for each model-vintage for each sample period. The comprehensiveness of the model will allow us to generate a complete picture of how gasoline prices affect the fuel efficiency economy of the whole fleet composition in a market.

Parameters of my model are then estimated by matching both set of these predicted shares with the corresponding empirical moments over time. My findings Comparisons between my preliminary findings and results from a static model indicate that the effects of gasoline prices on consumer's vehicle choices are underestimated in a static model, which is in line with our previous argument. The parameter estimates are then used to evaluate substantial fuel tax increases that have never been implemented before because they could be considered controversial and/or politically risky. The impact of the increase in fuel tax changes over time as the fleet to be replaced is increasingly more efficient as old clunkers get scrapped first. My preliminary results suggest that doubling the current tax rate would result in a decreasing trend of the increase of a city's fleet fuel efficiency after a mild initial impact: an immediate increase of 0.29 MPG, raising up to 1.01 MPG fades out to 0.34 MPG after seven years. Alternatively, a variable tax policy aimed at keeping the price of gasoline stable at $4 per gallon will increase fuel efficiency dramatically to 1.86 MPG in the first several years, remaining mostly stable thereafter, with an increased fuel efficiency of still 1.65 MPG after seven years.

In the current paper, I conduct a city-by-city analysis to study the dynamic effects of gasoline prices on consumer's vehicle choice due to the complexity of the problem. In the future, I will further do a comprehensive analysis that incorporate multiple markets. The data covers new and used vehicle registration data for nineteen markets (cities) in the United States. These markets range from big cites like Houston, TX to small towns like Lancaster, PA. By including the demographic variables, like household income, family size, I can model consumer heterogeneity in each market as an empirical nonparametric distribution of demographic and further identify how consumer's heterogeneous preferences over gasoline price dynamics vary with demographics.

References

[1] Austin, D., and Dinan, T. Clearing the air: The costs and consequences of higher cafe standards and increased gasoline taxes. *Journal of Environmental Economics and Management 50* (2005), 562–582.

[2] Bento, A. M., Goulder, L. H., Jacobsen, M. R., and von Haefen, R. H. Distributional and efficiency impacts of increased us gasoline taxes. *American Economic Review 99:3* (2009), 667–699.

[3] Berry, S., Levinsohn, J., and Pakes, A. Automobile prices in market equilibrium. *Econometrica 63*, 4 (July 1995), 841–90.

[4] Berry, S. T. Estimating discrete-choice models of product differentiation. *RAND Journal of Economics 25*, 2 (Summer 1994), 242–262.

[5] Busse, M. R., Knittel, C. R., and Zettelmeyer, F. Pain at the pump: How gasoline prices affect automobile purchasing. Unpublished manuscript.

[6] Davis, L. W., and Kilian, L. Estimating the effect of a gasoline tax on carbon emissions. *NBER Working Paper Series 14685* (2009).

[7] Davis, S., Diegel, S., and Boundy, R. Transportation energy data book: Edition 28. Tech. rep., Report ORNL-6984. Oak Ridge, TN: Oak Ridge National Laboratory, 2009.

[8] DeCicco, J. M. A fuel efficiency horizon for u.s. automobiles. *University of Michigan, Report for The Energy Foundation* (2010).

[9] Dubin, J. A., and McFadden, D. L. An econometric analysis of residential electric appliance holdings and consumption. *Econometrica 52*, 2 (March 1984), 345–62.

[10] Esteban, S., and Shum, M. Durable goods oligopoly with secondary markets: The case of automobiles. *Rand Journal of Economics* (2007).

[11] Goldberg, P. The effects of the corporate average fuel efficiency standards in the us. *Journal of Industrial Economics 46(1)*, 5673 (July 1998), 1–33.

[12] Gowrisankaran, G., and Rysman, M. Dynamics of consumer demand for new durable goods. *Unpublished manuscript, Boston University* (2009).

[13] Greenspan, A., and Cohen, D. Motor vehicle stocks, scrappage, and sales. *The Review of Economics and Statistics 81*, 3 (August 1999), 369–383.

[14] Haughton, J., and Sarkar, S. Gasoline tax as a corrective tax: Estimates for the united states, 1970-1991. *The Energy Journal 17*, 2 (1996), 103–126.

[15] Hughes, J. E., Knittel, C. R., and Sperling, D. Evidence of a shift in the short-run price elasticity of gasoline demand. NBER Working Papers 12530, National Bureau of Economic Research, Inc, Sept. 2006.

[16] Kleit, A. N. Impacts of long-range increases in the fuel economy (cafe) standard. *Economic Inquiry 42(2)* (2004), 279–94.

[17] Klier, T., and Linn, J. New vehicle characteristics and the cost of the corporate average fuel economy standard.

[18] Langer, A., and Miller, N. H. Automobile prices, gasoline prices, and consumer demand for fuel economy. EAG Discussions Papers 200811, Department of Justice, Antitrust Division, Dec. 2008.

[19] Li, S., Timmins, C., and von Haefen, R. H. How do gasoline prices affect fleet fuel economy? *American Economic Journal: Economic Policy 1*, 2 (August 2009), 113–37.

[20] Melnikov, O. Demand for differentiated durable products: the case of the u.s. computer printer market. *Unpublished manuscript, Cornell University* (2001).

[21] Mian, A., and Sufi, A. The effects of fiscal stimulus: Evidence from the 2009 "cash for clunkers" program.

[22] Nair, S., and Espey, M. Automobile fuel economy: What is it worth? 2004 Annual meeting, August 1-4, Denver, CO 20102, American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association), 2004.

[23] Nevo, A. Mergers with differentiated products: The case of ready-to-eat breakfast cereal industry. *RAND Journal of Economics 31*, 0303004 (Mar. 2000), 396–421.

[24] Nevo, A. A practitioner's guide to estimation of random-coefficients logit models of demand. *Journal of Economics & Management Strategy 9*, 4 (December 2000), 513–548.

[25] Parry, I. W. H., and Small, K. A. Does britain or the united states have the right gasoline tax? *American Economic Review 95*, 4 (September 2005), 1276–1289.

[26] Petrin, A. Quantifying the benefits of new products: The case of the minivan. *Journal of Political Economy 110* (2002), 705729.

[27] Rust, J. Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica 55* (1987), 999–1033.

[28] Schiraldi, P. Autobmobile replacement: A dynamic structural approach. Unpublished Manuscript, Boston University.

[29] Sivak, M., and Tsimhoni, O. Fuel efficiency of vehicles on us roads: 1923-2006. *Energy Policy 37*, 8 (August 2009), 3168–3170.

[30] Small, K. A., and Dender, K. V. Fuel efficiency and motor vehicle travel: The declining rebound effect. *The Energy Journal 28*, 1 (2007), 25–52.

[31] West, S. E. Distributional effects of alternative vehicle pollution control policies. *Journal of Public Economics 88*, 3-4 (March 2004), 735–757.