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ABSTRACT

Exploiting a rich data set of passenger vehicle registrations in twenty U.S. metropolitan statistical areas from 1997 to 2005, we examine the effects of gasoline prices on the automotive fleet's composition. We find that high gasoline prices affect fleet fuel economy through two channels: (1) shifting new and purchases towards more fuel-efficient vehicles, and (2) speeding the scrappage of older, less fuel-efficient used vehicles. Policy simulations based on our econometric estimates suggest that a 10% increase in gasoline prices from 2005 levels will generate a 0.22% increase in fleet fuel economy in the short run and a 2.04% increase in the long run.

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1. Introduction

How the composition of the U.S. vehicle fleet responds to changes in gasoline prices has important implications for policies that aim to address climate change, local air pollution, and a host of other externalities related to gasoline consumption.[3] We investigate this response. Exploiting a unique and detailed data set, we decompose changes in the vehicle fleet into changes in vehicle scrappage and new vehicle purchase decisions, and analyze how gasoline prices influence each of these choice margins. We then recover the fuel economy elasticities with respect to gasoline prices in both the short and long run.

In 2006, the United States consumed 7.6 billion barrels of oil. This represents roughly one-quarter of global production, with gasoline consumption accounting for 44% of oil consumption. The combustion of gasoline in automobiles generates carbon dioxide emissions, the predominate greenhouse gas linked to global warming, as well as local air pollutants such as nitrogen oxides and volatile organic compounds that harm human health and impair visibility. The costs associated with these environmental effects are generally external to gasoline consumers, leading many analysts to argue for corrective policies.

To address these externalities, a suite of policy instruments have been advanced, such as increasing the federal gasoline tax, tightening Corporate Average Fuel Economy (CAFE) standards, subsidizing the purchase of fuel efficient vehicles such as hybrids, and taxing fuel-inefficient "gas guzzling" vehicles. Several recent studies have compared gasoline taxes and CAFE standards and have concluded that increasing the gasoline tax is

[3] See Parry, Harrington, and Walls (2007) for a comprehensive review of externalities associated with vehicle usage and federal policies addressing those externalities.

more cost-effective (National Research Council, 2002; Congressional Budget Office, 2003; Austin and Dinan, 2005; Jacobsen, 2007). When evaluating the policy options, two important behavioral drivers are: (1) the utilization effect, or the responsiveness of vehicle miles traveled (VMT) to fluctuations in gasoline prices, and (2) the compositional effect, or the responsiveness of fleet fuel economy to gasoline price changes. Although a large body of empirical evidence on the magnitude of the utilization effect now exists (see Small and Van Dender (2007) and Hughes, Knittel, and Sperling (2008) for summaries and recent contributions), less evidence exists on the size of the compositional effect. This is the focus of our paper.

Existing studies that have attempted to quantify the elasticity of fuel economy to gasoline prices can be divided into two categories based on the methods and data used. Studies in the first group estimate reduced-form models where the average MPG of the vehicle fleet is regressed on gasoline prices and other variables by exploiting aggregate time-series data (Dahl, 1979; Agras and Chapman, 1999), cross-national data (Wheaton, 1982), or panel data at the U.S. state level (Haughton and Sakar, 1996; Small and Van Dender, 2007). Studies using time-series data or cross-sectional data are not able to control for unobserved effects that might exist in both temporal and geographic dimensions. Although a panel-data structure allows for that possibility, the average MPG used in panel-data studies (as well as other studies in this group) suffer from measurement errors. Because fleet composition data are not readily available, most of the previous studies infer the average MPG of the vehicle fleet based on total gasoline consumption and total vehicle miles traveled. However, data on vehicle miles traveled have well-known problems such as irregular estimation methodologies both across years and states (see Small and Van Dender (2007) for a discussion).

The second group of studies models household-level vehicle ownership decisions (Goldberg, 1998; Bento *et al*., 2008). A significant modeling challenge is to consistently incorporate both new and used vehicle holdings. Despite significant modeling efforts, Bento *et al*. (2008) have to aggregate different vintage models into fairly large categories in order to reduce the number of choices a household faces to an econometrically tractable quantity.[4] This aggregation masks substitution possibilities within composite automotive categories and therefore may bias the estimates of both demand elasticities with respect to price and the response of fleet fuel economy to gasoline prices toward zero.

Our study employs a qualitatively different data set and adopts an alternative estimation strategy. First, our data set measures the stock of virtually all vintage models across nine years and twenty Metropolitan Statistical Areas (MSAs) and hence provides a complete picture of the vehicle fleet's evolution. In contrast to the aforementioned reduced-form studies, the fuel economy distribution of vehicle fleet is therefore observed in our data. Second, the data allow us to control for both geographic and temporal unobservables, both of which are found to be important in our study. In contrast to the structural methods alluded to above, we make no effort to recover the household preference parameters that drive vehicle ownership decisions, and hence our results are robust to many assumptions made in those analyses. Finally, since we observe the fleet composition over time, we are able to examine how the inflow and outflow of the vehicle fleet are influenced by gasoline prices.

We first examine the effect of gasoline prices on the fuel economy of new vehicles

[4] Goldberg (1998) estimates a nested logit model by aggregating all used vehicles into one choice.

(i.e., the inflow of the vehicle fleet) based on a partial adjustment model. We find that an increase in the gasoline price shifts the demand for new vehicles toward fuel-efficient vehicles. We then study the extent to which gasoline prices affect vehicle scrappage (i.e., the outflow of the vehicle fleet). To our knowledge, this is the first empirical study that focuses on the relationship between gasoline prices and vehicle scrappage.[5] We find that an increase in gasoline prices induces a fuel-efficient vehicle to stay in service longer while a fuel-inefficient vehicle is more likely to be scrapped, *ceteris paribus*. With both empirical models estimated, we conduct simulations to examine how the fuel economy of the entire vehicle fleet responds to gasoline prices. Based on the simulation results, we estimate that a 10% increase in gasoline prices will generate a 0.22% increase in the short run (one year) and a 2.04% increase in the long run (after the current vehicle stock is replaced). We also find that sustained $4.00 per gallon gasoline prices will generate a 14% long-run increase in fleet fuel economy relative to 2005 levels, although this prediction should be interpreted cautiously in light of the relatively large out-of-sample price change considered and the Lucas critique (Lucas, 1976).[6]

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 investigates the effect of gasoline prices on fleet fuel economy of new vehicles. Section 4 examines how vehicle scrappage responds to changes in gasoline prices. Section 5 conducts simulations and discusses caveats of our study. Section 6 concludes.

[5] Previous papers on vehicle scrappage have focused on factors such as age, vehicle price and government subsidies to retirements of old gas-guzzling vehicles (Walker, 1968; Manski and Goldin, 1983; Berkovec, 1985; Alberini, Harrington, and McConnell, 1995; Hahn, 1995; Greenspan and Cohen, 1999).

[6] In particular, large and sustained gasoline price increases may introduce new demand and supply-side responses that would change the model parameters, which themselves might be functions of policy variables.

2. DATA

Our empirical analysis and policy simulations are based on vehicle fleet information in twenty MSAs listed in Table 1. The geographic coverage for each MSA is based on the 1999 definition by the Office of Management and Budget. These MSAs, well-representative of the nation as discussed at the end of this section, are drawn from all nine Census regions and exhibit large variation in size and household demographics. There are three data sets used in this study and we discuss them in turn.

The first data set, purchased from R.L. Polk & Company, contains vehicle registration data for the twenty MSAs. This data set has three components. The first component is new vehicle sales data by vehicle model in each MSA from 1999 to 2005. The second component is vehicle registration data (including all vehicles) at the model level (e.g., a 1995 Ford Escort) in each MSA from 1997 to 2000. Therefore, we observe the evolution of the fleet composition at the model level over these 4 years.[7] This part of the data includes 533,395 model-level records representing over 135 million vehicles registered during this period. The third component is registration data at the segment level (there are twenty-two segments) in each MSA from 2001 to 2005.[8] We observe 59,647 segment-level records representing over 170 million registrations during this period.[9] Our empirical analysis of new vehicles is based on the first part of this data set

[7] We ignore medium and heavy duty trucks and vehicles older than 1978 because the fuel economy information is not available for them. Since these vehicles account for less than 1% of total vehicle stock, our finding should not be significantly altered.

[8] There are 22 segments including 12 for cars (basic economy, lower mid-size, upper mid-size, traditional large, basic luxury, prestige luxury, basic sporty, middle sporty, upper specialty, prestige sporty), 4 for vans (cargo minivan, passenger minivan, passenger van, cargo van), 3 for SUVs (mini SUV, mid-size SUV, full size SUV), and 3 for pickup trucks (compact pickup, mid-size pickup and full size pickup).

[9] The stock data at the model level are very expensive. Facing the tradeoff of the level of aggregation and the length of the panel, we decided to purchase the stock data at the model level for years 1997 to 2000 and the stock data at the segment level for years 2001 to 2005. We discuss in Section 3 how we integrate the model and segment level data.

while that on vehicle scrappage is based on the second and third components of the data set.

Based on the changes in vehicle stock across time, we can compute vehicle survival probabilities at the model level from 1998 to 2000 and at the segment level from 2001 to 2005. The survival probability of a model in year *t* is defined as the number of registrations in year *t* over that in year *t*-1. The survival probability of a segment in a given year is defined similarly. These survival probabilities reflect two types of changes in the vehicle fleet. One is the physical scrappage of a vehicle and the other is the net migration of a vehicle in and out of the MSA, which might induce a survival probability larger than one. The average survival probability weighted by the number of registrations at the model level (369,507 observations) is 0.9504 with a standard deviation of 0.1098, while the average survival probability at the segment level (48,370 observations) is 0.9542 with a standard deviation of 0.0835. The standard deviations of the survival probabilities at the segment level being smaller reflect the aggregate nature of data at the segment level.

The second data set includes MSA demographic and geographic characteristics from various sources (observations in year 2000 are shown in Table 1). We collect median household income, population, and average household size from the annual American Community Survey. Data on annual snow depth in inches are from the National Climate Data Center. From the American Chamber of Commerce Research Association (ACCRA) data base, we collect annual gasoline prices for each MSA from 1997 to 2005. During this period, we observe large variations in gasoline prices both across years and MSAs. For example, the average annual gasoline price is $1.66, while the minimum was

$1.09 experienced in Atlanta in 1998 and the maximum was $2.62 in San Francisco in 2005. Figure 1 plots gasoline prices in San Francisco, Las Vegas, Albany, and Houston during the period. Both temporal and geographic variation is observed in the figure although geographic variation is relatively stable over time. The general upward trend in gasoline prices during this period can be attributed to strong demand together with tight supply. Global demand for oil, driven primarily by the surging economies of China and India, has increased significantly in recent years and is predicted to continue to grow. On the supply side, interruptions in the global oil supply chain in Iraq, Nigeria, and Venezuela, tight U.S. refining capacities, damage to that capacity as a result of gulf hurricanes, and the rise of boutique fuel blends in response to the 1990 Clean Air Act Amendments (Brown *et al*., 2008) have all contributed to rising and volatile gasoline prices.

The third data set includes vehicle attribute data such as model vintage, segment, make, and vehicle fuel efficiency measured by the combined city and highway MPG. The MPG data are from the fuel economy database complied by the Environmental Protection Agency (EPA).[10] We combine city and highway MPGs following the weighted harmonic mean formula provided by the EPA to measure the fuel economy of a model: MPG=1/[(0.55/city MPG) + (0.45/highway MPG)].[11] The average MPG is 21.04 with a standard deviation of 6.30. The least fuel-efficient vehicle – the 1987 Lamborghini Countach (a prestige sporty car) – has an MPG of 7.32, while the most fuel-

[10] These MPGs are adjusted to reflect road conditions and are roughly 15 percent lower than EPA test measures. EPA test measures are obtained under ideal driving conditions and are used for the purpose of compliance with CAFE standards.

[11] Alternatively, the arithmetic mean can be used on Gallon per Mile (GPM, equals 1/MPG) to capture the gallon used per mile by a vehicle traveling on both highway and local roads: GPM = 0.55 city GPM + 0.45 highway GPM. The arithmetic mean directly applied to MPG, however, does not provide the correct measure of vehicle fuel efficiency.

efficient one – the 2004 Toyota Prius (a compact hybrid) – has an MPG of 55.59.

With vehicle stock data and MPG data, we can recover the fleet fuel economy distribution in each MSA in each year.[12] The left panel of Figure 2 depicts the kernel densities of fuel economy distributions in Houston and San Francisco in 2005. The difference is pronounced, with Houston having a less fuel-efficient fleet. This is consistent with, among other things, the fact that San Francisco residents face higher gasoline prices, have less parking spaces for large autos, and tend to support more environmental causes. The right panel plots the kernel densities of fuel economy distributions in Houston in 1997 and 2005. The vehicle fleet in 1997 was more fuel-efficient than that in 2005 despite much lower gasoline prices in 1997. This phenomenon is largely driven by the increased market share of SUVs and heavier, more powerful and less fuel-efficient vehicles in recent years. For example, the market share of SUVs increased from 16 percent to over 27 percent from 1997 to 2005 despite high gasoline prices from 2001. The long trend of increasing share of SUVs and declining fleet fuel economy at the national level only started to reverse from 2006, mostly due to record high gasoline prices.

To examine whether the twenty MSAs under study are reasonably representative of the entire country, we compare the average MSA demographics and vehicle fleet characteristics with national data. As shown in Table 1, there is significant heterogeneity across the twenty MSAs in both demographics and vehicle fleet attributes. Nevertheless, the means of these variables for the twenty MSAs are very close to their national

[12] Although we only observe segment level stock data from 2001 to 2005, we can impute stock data at the model level during this period for vehicles introduced before 2001 based on the vehicle scrappage model estimated in Section 3. Along with these imputed model level stock data, the third component, which tells us the stock data for vehicles introduced after 2000, completes the vehicle stock data at the model level for years from 2001 to 2005.

counterparts. In Section 5.2, we examine how variation in demographics and gasoline prices affect the transferability of our MSA-level results to the entire nation.

3. Fuel Economy of New Vehicles

Our empirical strategy is to: (1) estimate the effect of gasoline prices on both the inflow (new vehicle purchase) and the outflow (vehicle scrappage) of the vehicle fleet, and (2) simulate the would-be fleet of both used and new vehicles under several counterfactual gasoline tax alternatives. In this section, we study how gasoline prices affect the fleet fuel economy of new vehicles. We examine the effect of gasoline prices on vehicle scrappage in the next section.

We separately investigate new vehicle purchase and vehicle scrappage decisions. To preserve robustness, our approach allows each choice margin to be driven by different factors (e.g., credit availability, macroeconomic conditions) through different empirical models. Although these two decisions may very well be inter-related, modeling both the new vehicle market and used vehicle market simultaneously presents a significant empirical challenge as we discussed in the introduction. For example, Bento *et al*. (2008) have to aggregate different vehicle models into fairly large categories for the sake of computational feasibility in an effort to model new vehicle purchase and used vehicle scrappage simultaneously. However, in doing so, potentially useful information about within-category substitution has to be discarded. Although we perform separate analyses of new vehicle purchase and used vehicle scrappage decisions, we try to control for possible interactions between the choice margins on our tax policy simulations.

3.1. Empirical Model

Because of behavioral inertia arising from adjustment costs or imperfect information, we specify a partial adjustment process that allows the dependent variable (i.e., new purchases of a particular vehicle type) to move gradually in response to a policy change to the new target value. Specifically, the one-year lagged dependent variable is included amongst the explanatory variables. This type of model can be carried out straightforwardly in a panel data setting and has been employed previously in the study of the effect of gasoline prices on travel and fleet fuel economy. For example, both Haughton and Sarkar (1996) and Small and Van Dender (2007) apply this type of model to the panel data of average fleet MPG at the U.S. state level, and Hughes et al. (2007) employ it in a model of U.S. gasoline consumption.

Compared with these previous studies, our data set is much richer in that we have registration data at the vehicle model level that provide valuable information about how changes in the gasoline price affect substitution across vehicle model. However, the empirical model based on the partial adjustment process cannot be applied directly to the vehicle model-level data because vehicle models change over time. On the other hand, aggregating data across models at the MSA level would discard useful information on vehicle substitution. With this in mind, we generate an aggregated data panel in the following way. In each of the four vehicle categories (cars, vans, SUVs, and pickup trucks), we pool all the vehicles in the segment in each of the twenty MSAs from 1999 to 2005 and find the q-quantiles of the MPG distribution. Denote c as an MPG-segment cell that defines the range of MPGs corresponding to the particular quantile and denote t as year. Further denote N_{ct} as the total number of vehicles in the MPG-segment cell c at year t, with MSA index m suppressed.

With this panel data, we estimate the following model:

$$\ln(N_{ct}) \;=\; \theta_0 + \theta_1 \ln(N_{c,t-1}) + (\theta_2 \frac{1}{MPG_{c,t}} + \theta_3) GasP_t + Other\ Controls + \xi_{ct}$$

where the coefficient on the price of gas ($GasP_t$) is allowed to vary with the inverse of the cell's MPG. Noting that $\frac{GasP_t}{MPG_{c,t}}$ equals dollars-per-mile ($DPM_{c,t}$), we can re-write this expression as follows:

$$\ln(N_{ct}) \;=\; \theta_0 + \theta_1 \ln(N_{c,t-1}) + \theta_2 DPM_{c,t} + \theta_3 GasP_t + Other\ Controls + \xi_{ct} \quad (1)$$

Since the lagged dependent variable is one of the explanatory variables, serial correlation in the error term would render this variable endogenous. We allow the error term to be first-order serially correlated with correlation parameter γ:

$$\xi_{ct} = \gamma \xi_{c,t-1} + \nu_{ct}$$

where ν_{ct} is assumed to be independent across t. With this serial correlation structure, the model can be transformed into:

$$\ln(N_{ct}) = \gamma \ln(N_{c,t-1}) + \theta(Z_{ct} - \gamma Z_{c,t-1}) + \nu_{ct}, \qquad (2)$$

where Z_{ct} is a vector of all the explanatory variables in equation (1), including the lagged dependent variable, and θ represents the vector of all coefficients. θ and γ can be estimated simultaneously in this transformed model using the least squares method, where we take into account both heteroskedasticity and cross-cell correlation of ν_{ct} in estimating the standard errors.

Another concern in finding an appropriate empirical model is to describe how current and past gasoline prices affect consumer decisions. An implicit assumption in the literature on new vehicle demand (Berry, Levinsohn, and Pakes, 1995; Goldberg, 1995; Bento *et al*., 2008) is that gasoline prices follow a random walk, which implies that only current gasoline prices matter in purchase decisions. This assumption can have important implications on long-run policy analysis. For example, should past gasoline prices matter (as would be the case if gasoline prices exhibited mean-reversion), studies with the random walk assumption would under-estimate the long-run effect of a permanent gasoline tax increase. While some empirical evidence suggests that recent gasoline prices follow a random walk instead of a mean-reverting pattern (Davis and Hamilton, 2004; Geman, 2007), we do consider alternative specifications that explicitly include the role played by lagged gasoline prices in current purchase decisions. We find that including lagged gasoline prices has very little impact on our policy simulation results and elasticity estimates. Due to the strong collinearity in gasoline price variables across years (after the MSA-constant time variation in gasoline prices is captured by year dummies), the signs of the parameter estimates on lagged price variables tend to bounce from positive to negative and the parameters exhibit large standard errors. We do not report those parameter estimates here for the sake of brevity, but we do discuss the elasticities they imply in Section 5.1.[13]

3.2. Estimation Results

We define MPG cells based on twenty quantiles of the MPG distribution.[14] Due to the discrete nature of the spectrum of MPGs from available vehicle models, there are in total 68 cells generated for the four vehicle categories.[15] The estimation results are presented in Table 2 with various control variables. Columns 1 and 2 report the results from the preferred specification, where the most controls are included. In all the specifications except the second (where the least controls are included), we cannot reject the first-order correlation coefficient γ being zero. In the first specification, γ is estimated at 0.025 with a standard error of 0.157, while in the second specification it is estimated at -0.115 with a standard error of 0.024. Therefore, all the results except for the second specification are for the model where serial correlation is assumed to be zero, allowing a longer panel to be used.

In the first specification, the coefficient estimate on the lagged dependent variable, $ln(N_{c,t-1})$, is 0.068 with a standard error of 0.006. This implies a modest partial adjustment process in new vehicle purchases. The short-run partial effect of gasoline prices on the number of new vehicles is: $\frac{\partial N_{ct}}{\partial GasP} = [1.145\text{-}(26.70/MPG)]N_{ct}$. This implies

[13] Estimation results including lagged gas prices are available from the authors upon request.
[14] We also carried out regressions based on 10-quantiles and 30-quantiles. Results from both are similar to what are reported here. The regression based on 10-quantiles produces marginally smaller effects of gasoline prices, consistent with our conjecture that data aggregation tends to bias the effects downwards by discarding information about cross-vehicle substitution within the aggregated category.
[15] There are only 16 cells generated for pickup trucks from the twenty quantiles because, for example, the 5th percentile and the 10th percentile of the MPG distribution for pickup trucks is the same.

that an increase in the gasoline price will increase the sales of new vehicles with MPG higher than 23.31 (i.e., the 60th percentile of the MPG distribution in the twenty MSAs), and reduce the sales of less fuel-efficient models. The long-run partial effect of gasoline prices on the number of new vehicle registrations is the short-run effect divided by (1-0.068). We note in passing that the empirical model mainly captures the effect of gasoline prices on the demand side. The supply-side effect (in particular, the effect on product offerings) is likely to take several years to be realized, which would suggest a more dramatic departure between the short-run and long-run effects. Nevertheless, a serious examination of the supply-side effect necessitates a more sophisticated, computationally-heavy model and richer firm-level data, since product offering in the auto industry is an inherently dynamic problem involving strategic considerations.

Comparison across specifications demonstrates the importance of various unobserved effects. Specifications 2 and 3 show that controlling for heterogeneity across MPG cells dramatically reduces the coefficient estimate on $ln(N_{c,t-1})$, which in turn has important implications on how past gasoline prices affect consumer decisions. The estimation results from specifications 3 and 4 illustrate that, without controlling for the temporal unobservable, the effect of gasoline prices on new vehicle demand would be under-estimated. The downward bias is likely caused by the fact that the new vehicle fleet became less fuel-efficient in the early years largely due to the increasing popularity of SUVs despite rising gasoline prices. We control for geographic unobservables (above those included MSA demographics) with census region dummies.[16]

[16] Ideally, we would like to include MSA dummies in the regression. However, because cross-MSA variation in gasoline prices, largely due to differences in state and local gasoline taxes and transportation costs, are fairly stable over time, MSA dummies would subsume the cross-sectional variation in the gasoline variable and prevent us from precisely estimating the parameter on the gasoline price.

It is interesting to note what helps to identify the response of new vehicle purchases to gasoline prices. The response is dictated by the coefficients on *DPM* and *GasP* in equation (1). With both year and region dummies included in the regression, the identification of the coefficient on *GasP* primarily relies on cross-sectional variations of new vehicle demand in response to changes in gasoline prices across both census regions and MSAs in the same region. Since this cross-sectional variation reflects persistent differences in gasoline prices across areas (e.g., due to differences in local taxes, transportation costs, and market conditions), our estimated effect of gasoline prices on new vehicle demand captures the response of fleet fuel economy to permanent (instead of transitory) price changes. The identification of the coefficient on *DPM*, however, relies not only on cross-sectional variation due to differences in gasoline prices but also on cross-model variation arising from the fact that the demand response to changes in gasoline prices varies across vehicles with different fuel efficiency.

4. The Evolution of the Stock of Used Vehicles

The previous section examined the effect of gasoline prices on the flow of new vehicles into the fleet and found that an increase in the gasoline price would increase the purchase of fuel-efficient vehicles while reducing that of fuel-inefficient vehicles. To complete the picture of how gasoline prices affect the whole vehicle fleet, we investigate the impact of gasoline price changes on the evolution of used vehicles. In particular, we are interested in how gasoline prices affect the flow of vehicles out of the fleet through vehicle scrappage.

4.1. Empirical Model

We define vehicle scrappage as the discontinuation of a vehicle's registration due to physical breakdown or dismantling.[17] Another reason for discontinuation of service at the national level is export to other countries.[18] Both physical breakdown and vehicle migration to other countries are relevant for the study of how gasoline prices affect U.S. fleet fuel economy. When it comes to registration data at the MSA level, the discontinuation of a vehicle registration in an MSA can arise from physical breakdown and vehicle migration due to *inter-MSA* resale or relocation of the owner. The latter effect has the potential to bias our estimated effect of gasoline price on scrappage; we return to this potential problem below.

To examine changes in vehicle registration, let i denote a model of a particular vintage, let t denote a year starting from 1997, and let m denote an MSA. With m suppressed, the change of vehicle stock from period $t-1$ to period t:

$$\frac{N_{jt}}{N_{j,t-1}} = P_{jt}(X_{jt}, \beta) + \varepsilon_{jt}, \qquad (3)$$

where N_{jt} denotes the vehicle stock at the end of year t. X_{jt} is a large vector of vehicle attributes of model j and regional characteristics of the MSA where model j is registered in year t. A key variable of interest in X is the gasoline price. β is a vector of parameters

[17] Greenspan and Cohen (1999) identify crime, accidents, and wear-and-tear as primary reasons for physical breakdown or dismantling.

[18] There were 52,759 used vehicles exported to Mexico through Santa Teresa Port of Entry in New Mexico alone in 2004. As Davis and Kahn (2008) document, these trade flows have risen dramatically since 2005 due to used-car tariff reductions between the U.S. and Mexico associated with the North American Free Trade Agreement (NAFTA).

to be estimated. P_{jt} is the survival probability of model j in year t, which is explained by X, while ε_{jt} captures measurement error and any other changes of vehicles registration that are unaccounted for by observed variables.

Although we are more interested in the effect of gasoline prices on vehicle scrappage from the standpoint of policy-relevance (as opposed to vehicle migration across MSAs), the source of registration discontinuation is not identified in our data. To minimize the effect of vehicle migration on our results, we focus on old vehicles (i.e., vehicles with more than 10 to 15 years of services) in our empirical analysis. The underlying assumption is that although migrations of these old vehicles across MSAs may occur, they are not systematically related to gasoline prices. To the extent that correlation between the gasoline price and used vehicle migration arises from re-sales made in order to take advantage of the fact that fuel-efficient used vehicles may have a higher valuation in MSAs with higher gasoline prices, the correlation should be weaker for old vehicles because the difference in vehicle valuation (which should be proportional to the length of remaining life span of the vehicle) is more likely to be too small to cover transport and sales transactions costs.

To estimate the model, we assume that the error term is mean independent of variables in X: $E(\varepsilon_{jt} \mid X_{jt}) = 0$. A potential concern with this assumption is the endogeneity of the gasoline price due to unobservables (e.g., temporal or geographic unobservables such as new car prices and offerings) that are correlated with both vehicle scrappage decisions and gasoline prices. To address this, we include various time and region dummies as well as MSA demographic variables in the vector X. We should point out that since our used car analysis is at the vehicle model level, simultaneity between vehicle scrappage and gasoline prices should be less of a concern. It is unlikely for a model-specific error term, ε_{jt}, in vehicle scrappage to be significant enough to affect gasoline prices.

In the estimation, we assume that survival probabilities take a logistic form:

$$P_{jt} = \frac{\exp(X'_{jt}\beta)}{1+\exp(X'_{jt}\beta)}.$$

Nonlinear least squares can be used to recover the parameter vector β. However, this method can only be applied to 1997-2000 where detailed stock data at the model level are available. In years from 2001 to 2005 (i.e., the period of rapid rising gasoline prices), we observe stock data only at the segment level; hence the model level survival probability, P_{jt}, cannot be obtained from the data for this period. In order to take advantage of these segment-level data and the gasoline price variation during this period, we employ a generalized method of moments estimator. We set up two sets of moment conditions based on the two parts of the data. Denote J_t as the total number of models in year t. Bearing in mind that we suppress market index m and hence the aggregation over markets, the first set of moments based on equation (3) is:

$$M_1(\beta) = \frac{1}{\sum_t J_t} \sum_{t=1998}^{2000} \sum_{j=1}^{J_t} X'_{jt} \left[N_{jt} - N_{j,t-1} P_{jt} \right]. \tag{4}$$

This set of moment conditions is taken to the model-level data from 1997 to 2000 while the second set is taken to the segment-level data from 2001 to 2005.

Intuitively, to form the second set of moments, we take vehicle stocks at the model level in 2000 and simulate forward based on predicted survival probabilities. This yields model level stock data for the years 2001 to 2005 for vehicles that existed in 2000. We then aggregate these predicted model-level stock data to the segment-level and match those segment-level predictions to their observed counterparts. To that end, let *s* denote a segment of certain vintage and S_{t-1} denote the total number of segments in year *t-1*. The total registration of all models in segment *s* at year *t*,are given by:

$$N_{st} = \sum_{j \in \mathbf{S_{t-1}}} N_{jt} = \sum_{j \in \mathbf{S_{t-1}}} N_{j,t-1}(P_{jt} + \varepsilon_{jt}). \tag{5}$$

The number of vehicle registrations in segment *s* after *k* years, $N_{s,t+k}$ is given by:

$$N_{s,t+k} = \sum_{j \in \mathbf{S_{t-1}}} N_{j,t+k} = \sum_{j \in \mathbf{S_{t-1}}} N_{j,t-1}\Big[\prod_{h=0}^{k}(P_{j,t+h} + \varepsilon_{j,t+h})\Big]. \tag{6}$$

In order to forecast vehicle registration in the future, we assume that the error term exhibits first-order serial autocorrelation:

$$\varepsilon_{jt} = \rho \varepsilon_{j,t-1} + e_{jt},$$

where e_{jt} is assumed to be i.i.d. across both *j* and *t*. Moreover, we assume that $E(e_{j,t+h} \mid X_{jt}) = 0$ for any non-negative *h*. This assumption is implied by the strict exogeneity assumption of the explanatory variables (i.e., $E(\varepsilon_{j,t+h} \mid X_{jt})$ = 0 for any h) and is stronger than the contemporaneous exogeneity (i.e., $E(\varepsilon_{jt} \mid X_{jt})$ = 0) required by the first set of moment conditions.

The prediction of the vehicle registration in segment s after k years, $N_{s,t+k}$ is (e.g., projecting segment registrations in 2005 based on the model-level data, $N_{j,t-1}$, in 2000):

$$\tilde{N}_{s,t+k} = \sum_{j \in \mathbf{S_{t-1}}} \tilde{N}_{j,t+k} = \sum_{j \in \mathbf{S_{t-1}}} N_{j,t-1} \Big[\prod_{h=0}^{k} (P_{j,t+h} + \rho^{h+1} \varepsilon_{j,t-1}) \Big]. \tag{7}$$

The difference between $N_{s,t+k}$ and its forecast, $\tilde{N}_{s,t+k}$ arises from the error terms, e_{jt}, $e_{j,t+1}$, …, $e_{j,t+k}$. Denote the parameter vector B = [β ρ], the second set of moments is then defined as:

$$M_2(B) = \frac{1}{\sum_t S_t} \sum_{t=2001}^{2005} \sum_{s=1}^{S_t} \bar{X}_s' \Big[N_{st} - \tilde{N}_{st} \Big], \tag{8}$$

where $\bar{X}_s$ is a vector of weighted mean of product attributes for all the products in segment s using the stock data in 2000 as weight. $\tilde{N}_{st}$ is the stock of segment s at year t projected from the observed data in 2000 following the equation.

To estimate B, we stack both sets of moment conditions to form the criterion function. The GMM estimator $\hat{B}$ minimizes:

$$J = M(B)'WM(B) = \begin{pmatrix} M_1(\beta) \\ M_2(B) \end{pmatrix} \begin{pmatrix} W_1 & 0 \\ 0 & W_2 \end{pmatrix} \begin{pmatrix} M_1(\beta) \\ M_2(B) \end{pmatrix}. \quad (9)$$ [19]

Denote $G = E[\nabla_B M(B)]$ and $\Omega = E[M(B)M(B)']$, the asymptotic variance of $\sqrt{n}(\hat{B} - B)$ is $(G'WG)^{-1}G'W\Omega WG(G'WG)^{-1}$. We estimate B and its asymptotic variance using a two-step procedure where the first step sets $W = I$ and provides consistent estimates for B and the optimal weighting matrix $W = \Omega^{-1}$. The second step re-estimates the model using the consistent estimate of the optimal weighting matrix obtained in the first step. With the parameter estimate $\hat{B}$, we then can predict the stock data at the model level in years from 2001 to 2005 for the models that are available in 2000. Combining these predicted model-level data with new vehicle registration data from 2001 to 2005 described in the data section, we then have a complete vehicle stock data at the model level in all years.[20]

4.2. Estimation Results

Table 2 presents parameter estimates of the vehicle survival model with various specifications. The first four specifications focus on vehicles older than ten years.

[19] Alternatively, we can use a serial autocorrelation structure in forming the first set of moment conditions. The new moment conditions would be $M_1(B) = \frac{1}{\sum_t J_t} \sum_{t=1999}^{2000} \sum_{j=1}^{J_t} X'_{jt} \left[N_{jt} - N_{j,t-1}(P_{jt} + \rho\varepsilon_{t-1}) \right].$ Notice t in the new conditions would have to start from 1999 instead of 1998 as shown in equation (2), implying a shorter panel to be used in forming the moment conditions. Both methods would give consistent parameter estimates under the strict exogeneity assumption and the serial correlation structure.

[20] Another strategy to predicting missing model level data from segment level data for 2001-2005 would involve aggregating the 1997-2000 model level data to the segment level data and estimating a scrappage model using segment level data from years 1997 through 2005. However, a complication with this strategy is that we do not observe segment level MPGs nor do we have the weights necessary to construct segment level MPGs from observable model level MPGs. Therefore, whatever segment level MPGs we would end up using would suffer from measurement error that could significantly bias parameter estimates.

Estimation of the first three specifications are based on the two sets of moment conditions, taking advantage of both 203,014 model-level observations and 19,360 segment-level observations. The fourth specification is only based on the first set of moment conditions and the model-level observations and does not specify the serial correlation structure of the error term. The fifth specification focuses on vehicles older than fifteen years with 105,734 model-level observations and 10,560 segment-level observations.

We go to great lengths to control for unobservables along various dimensions by including a long list of dummy variables. We include vehicle segment dummies, make dummies, as well as their interactions terms with vehicle age to control for variations in ownership cost and resale value across models.[21] MSA demographic variables along with region dummies are used to control for cross-sectional heterogeneity. Year dummies and the interaction between a time-trend and vehicle category dummies are used to capture temporal unobservables such as new product offering and prices that may affect vehicle scrappage.

Columns 1 and 2 report the estimation results for the preferred specification where the most control variables are used. Most of the parameters are estimated very precisely. The partial effect of gasoline prices on vehicle survival is of particular interest because it is directly related to how gasoline prices affect the fuel economy of used vehicles. A rise in the gasoline price increases the operating cost of a fuel-inefficient vehicle more than a fuel-efficient one. Therefore, a fuel-inefficient vehicle is more likely to get scrapped than its fuel-efficient counterpart, *ceteris paribus*. Given that survival probabilities take the

[21] Since many models are observed in numerous MSAs and over many years, we could conceivably add model dummies to control for model-level unobservables in our scrappage estimation. The number of models (e.g., 4,177 models with age larger than 10) is, however, too large to make this method practical given that within-group demeaning as a way of controlling for fixed effects does not apply in the nonlinear framework.

logistic functional form, the partial effect of gasoline prices on the survival of vehicles older than 10 years equals [0.638-(18.362/*MPG*)] P_{jt} (1- P_{jt}), where P_{jt} is the survival probability of model *j* in year *t*. For vehicles with MPG higher than 28.73 (about the 80th percentile of the MPG distribution of vehicles older than ten years in the twenty MSAs), the partial effect is positive, which means that an increase in the gasoline price would raise the survival probabilities of those vehicles. On the other hand, an increase in the gasoline price would reduce the survival probabilities of vehicles with MPG less than 28.73. We note that the identification of the effect of gasoline prices on vehicle survival, similar to the identification of the effect on new vehicle demand in the previous section, relies not only on temporal and cross-sectional variation in vehicle scrappage due to differences in gasoline prices but also on cross-model variations from the fact that vehicles with different fuel economy respond to changes in gasoline prices differently.

The comparison of the first three specifications shows the importance of controlling for both temporal and geographic unobservables. In particular, ignoring the temporal unobservables would lead to the over-estimation of the effect of gasoline prices on vehicle scrappage while ignoring the geographic unobservables does the opposite. The fourth specification only employs the first set of moments based on the model-level data and predicts 29.12 (versus 28.73 in the first specification) as the MPG level at which the effect of gasoline prices on vehicle survival changes direction. The results from the fifth specification, which is estimated using vehicles in service longer than fifteen years, suggest that an increase in the gasoline price would prolong the life of vehicles with MPGs higher than 24.31, while it would shorten that of less fuel-efficient vehicles.

To see the economic significance of the effect of gasoline prices on vehicle survival, we present the elasticities of survival probability with respect to gasoline prices in Table 4. The first row in Panel 1 reports the weighted average measures for all vehicles older than ten years in 2000, where the weights are the number of registrations of each model. The average survival probability for these vehicles is 89 percent while the average elasticity is -0.023. [22] This average, however, masks significant cross-vehicle heterogeneity that arises partly from differences in fuel efficiency. To see this, we pick two models: a 1985 Honda Civic with an MPG of 39.7, and a 1985 Chevy Impala with an MPG of 21.1. Based on the parameter estimates, a one-percent increase in gasoline prices would increase the survival probability of the Honda Civic by 0.051 percent while reducing that of the Chevy Impala by 0.038 percent in Houston. As gasoline prices in San Francisco are much higher than those in Houston, the heterogeneity across vehicles is even stronger in San Francisco as shown in the table. It is also interesting to note the variation in survival probabilities across these two MSAs. The fuel-efficient Honda Civic has a higher survival probability than the Chevy Impala in San Francisco while the opposite is true in Houston. This type of variation provides an important source for the identification of the effect of gasoline prices on vehicle survival. The results in Panel 2 of Table 4 are based on the parameter estimates from the fifth specification, where we assume that gasoline prices affect scrappage but not migration for vehicles already in service longer than fifteen years. The two panels provide qualitatively the same estimates for the survival elasticities, with Panel 2 showing that the gasoline price has a stronger positive effect on the survival of fuel-efficient vehicles but a weaker negative effect on

[22] The 95% confidence intervals based on parametric bootstrapping are provided in the table. Because the estimation of the vehicle survival model is computationally intensive, nonparametric bootstrapping (which involves repeated estimation of the model) is not feasible. Parametric bootstrapping only requires that the model to be estimated once, but it does impose stronger assumptions on the data generating process.

that of fuel-inefficient vehicles.

5. Simulations

In the previous two sections, we found that gasoline prices have statistically significant effects on both the flow into and out of the vehicle fleet. The goal of this section is to examine the response of fleet fuel economy to gasoline price. To that end, we conduct simulations that combine the results of the two empirical models.

5.1. Impacts of Gasoline Tax Increases

We first simulate the short-run and long-run responses of fleet fuel economy distribution to alternative gasoline tax policies – specifically, an increase in the federal gasoline tax of $0.25, $0.60, $1.00 or $2.40. Among industrial countries, the U.S. has the lowest gasoline tax (41 cents per gallon on average including federal, state and local taxes). Meanwhile, Britain has the highest gasoline tax of about $2.80 per gallon. Parry and Small (2005) estimate the optimal gasoline tax in the U.S. is roughly $1.01 per gallon, so a 60 cent gasoline tax increment is needed to reach the optimal level. Williams (2005) estimates an optimal tax of $0.91 per gallon. Although we by no means believe that $2.80 dollar gasoline tax is politically feasible in the U.S., we consider the $2.40 gasoline tax increase for the purpose of illustration.[23] Note that the recent run-up in gasoline prices in the United States can be viewed as being equivalent to an increase in the gas tax between $1.00 and $2.40, which is passed-on fully to consumers.

[23] Following Bento *et al*. (2008), we assume that the entire tax burden falls on consumers in the simulations. That is, the price increase equals the tax increase. This amounts to the assumption that gasoline is produced by a perfectly competitive industry exploiting a constant return to scale technology. To the extent that gasoline producers have to bear some tax burden, e.g., due to the imperfect competitive nature of the industry, the results in the simulation provide upper bounds of the true effects of gasoline tax increases.

Table 5 reports the effect of gasoline tax increases on the average MPG of new vehicles, used vehicles, and all vehicles in 2005. Panel 1 presents the short-run impacts in a scenario where 2005 is the first year of tax increases. The results show that the significant effect of gasoline prices on vehicle scrappage for vehicles older than ten years translates into a very small impact on the average fuel economy of used vehicles. The impact of a tax increase on fleet fuel economy comes, therefore, mainly through the inflow of new vehicles. The short-run elasticities of average MPG with respect to gasoline prices are 0.191, 0.006, and 0.022 for new vehicles, use vehicles, and all vehicles, respectively.

To examine how the impact of a gasoline tax increases plays out over a longer time period, we look next at a scenario where the gasoline tax increase begins in 2001. The effect on the vehicle stock is significantly greater because it incorporates the cumulative effects on new vehicles starting from 2001. For example, the elasticity for all vehicles increases from 0.022 to 0.101. In an even longer term, new vehicles will continue to replace old vehicles, so the effect of gasoline prices on the fuel economy of the whole fleet beyond the fifth year will be increasingly dictated by its effect on the fuel economy of new vehicles. Therefore, we can interpret the elasticity for new vehicles, 0.204, as the long-run effect of gasoline taxes on fleet fuel economy.[24]

Based on our alternative specification where we included lagged gasoline prices variables (both dollars-per-mile and gasoline price variables) up to three years in the

[24] Linn and Klier (2007) obtain their estimates of the long-run effect of a gasoline tax also through the response of new vehicle MPG to changes in the gasoline price. Using U.S. monthly sales data from 1980 to 2006, they find smaller responses than ours (e.g., a one-dollar increase in the gasoline price increases the average MPG of new vehicles in 2006 by 0.5MPG). To the extent that consumers view a monthly price change as more transitory than that observed on a yearly basis, the response in new vehicle purchase to changes in gasoline price would be smaller using monthly data.

model for new vehicles, simulations show that the short-run and long-run elasticities of the average MPG for new vehicles with respect to gasoline prices are 0.211 and 0.212 with the 95% confidence interval of [0.095 0.346] and [0.139 0.296], respectively. These two elasticity estimates are very close to those from our baseline model (i.e., 0.191 and 0.204) where only the current gasoline price variables were included. Nevertheless, the confidence intervals in the model with lagged gasoline price variables are visibly larger because the standard errors of the coefficient estimates are much larger due to the high multicollinearity in the gasoline price variables across years.

5.2. Heterogeneity in Fuel Economy Elasticity

The fuel economy elasticities in the previous section are estimated for vehicles in the twenty MSAs in year 2005. This section examines the heterogeneity of fuel economy elasticities by studying how they vary with the gasoline price and other demographics. This question has important implications for how our estimates can be used in policy analysis at the national level and/or in a different period. For example, given the sharp increases in gasoline price since 2005, it is interesting to ask whether fuel economy elasticities have gone up significantly.

Panel 1 of Table 6 shows the summary statistics of the elasticity estimates for each MSA in each year from 1999 to 2005. The elasticities for all vehicles are based on contemporaneous gasoline price changes; therefore, they reflect the short-run effects of gasoline prices on fleet fuel economy. The elasticities for new vehicles, however, are estimated based on permanent price changes and can be regarded as long-run effects. Significant variations in these estimates are observed. Moreover, the average elasticities both for all vehicles and for new vehicles over the seven-year period are smaller than those in 2005 as shown in Table 5.

To examine the sources of variation in fuel economy elasticities, we perform linear regressions where the dependent variable is the logarithm of estimated elasticities. We are interested in how the gasoline price and other demographic variables affect these elasticities while controlling for unobserved regional and temporal effects. Panel 2 of Table 6 reports parameter estimates and their robust standard errors. Since the gasoline price variable is also in the logarithm form, the coefficient estimates suggest that doubling gasoline prices would increase the short-run fuel economy elasticity by 68.7% while increasing the long-run fuel economy elasticity by 86.9%. Moreover, differences in the demographic variables have very small effects on the fuel economy elasticities.

Given that the average gasoline price in the twenty MSAs in 2005 was only slightly higher than the national average (2.34 versus 2.24) and other MSA characteristics are quite close to the national average as shown in Table 1, we expect the elasticity estimates based on the data from the twenty MSAs in 2005 shown in the previous section should be good proxies for the national estimates. Considering that gasoline prices in the U.S. passed $4.00 per gallon in 2008 (a 71 percent from $2.34), our model predicts the short and long-run fuel economy elasticities would increase by 48.7 and 61.7 percent to 0.033 and 0.330 from 0.022 and 0.204, respectively, holding all the other factors the same.

5.3. Alternative Specifications

Given the findings in Section 3 that lagged gasoline prices matter little in consumers purchase decisions, and that the inflow of new vehicles is the major channel through which gasoline prices affect fleet fuel economy, we re-examine the impact of those prices on the fuel economy of new vehicles using some alternative specifications.

Instead of aggregating data into a panel setting as in Section 3 in order to estimate an empirical model based on a partial adjustment process, we now use model-level observations directly. In particular, we estimate linear equations where the dependent variable is the vehicle MPG while the explanatory variables include the gasoline price and other controls.

Table 7 presents parameter estimates and robust standard errors for four specifications. The key explanatory variable is the gasoline price. The logarithm of the MPG is used in the first three regressions while the fourth one uses the linear form.[25] The last row reports the estimates of the fuel economy elasticity with respect to the gasoline price. The comparison of the first three regressions yields the same finding as those from Section 3 – without controlling for temporal unobservables, the effect of gasoline prices would be under-estimated while the opposite is true if geographic unobservables were not controlled for. The estimate of the fuel economy elasticity from the first regression is 0.143, compared to 0.148 based on the partial adjustment process for all new vehicles from 1999 to 2005 as reported in Panel 1 of Table 5.

5.4. Discussion and Caveats

Based on the simulation results in Tables 5 and 6, the average short and long-run elasticities of fuel economy with respect to the gasoline price over the period from 1999 to 2005 is 0.014 and 0.148, respectively. We find that the elasticities increase with the gasoline price. For example, the short-run and long-run elasticites increase to 0.022 and

[25] The gasoline price used in the estimation is the current gasoline price plus 0.068 times the gasoline price in the last year. We also estimate some other specifications. The regressions where the current gasoline price is used yield marginally smaller coefficients on the gasoline price variable. The log-linear specification whose results are report here, provides higher R^2 than log-log and linear-linear specifications.

0.204 in 2005 when gasoline prices were highest during the seven-year period. Compared to the estimates cited in the introduction, our estimates are smaller than those from reduced-form studies and larger than those from structural studies. In addition to measurement error in the constructed dependent variable (i.e., the average fleet MPG), reduced-form studies often base their estimations on aggregate state or national level data and are limited in their ability to control for unobserved temporal and geographic effects, which we find to be important. Studies that do not control for unobserved effects have much higher estimates – Dahl (1979) and Wheaton (1982) obtain the short-run fuel economy elasticity of 0.21 and 0.33, respectively. Although both Haughton and Sarkar (1996) and Small and Van Dender (2007) use fixed effects at the state level, they do not control for unobserved time-varying effects. Relative to these studies, our results are closest to the short-run and long-run fuel economy elasticity of 0.04 and 0.21 in Small and Van Dender (2007). Studies using a structural approach have to aggregate similar vehicles into one composite product to keep tractability in estimation. The aggregation could bias the fuel economy elasticity toward zero by discarding the substitution across products within the categories used for aggregation. Goldberg (1998) obtains a long-run fuel economy elasticity of 0.05 according to her results in section IV(ii). Based on Table 5-2 in their appendix, Bento *et al*. (2008) find short-run and long-run elasticities of 0.005 and 0.009, respectively, for an average 2001 gasoline price of $1.49 per gallon. The implicit assumption in these structural studies that only current gasoline prices matter in consumer decisions may also contribute to the lower estimates of fuel economy elasticities.

Two caveats are worth mentioning in relation to our analysis. The first one, not unique to our study, concerns the effect of gasoline prices on the supply side, which may have important bearings on the long-run effect of the gasoline price. In our empirical models, we control for temporal unobservables by including year dummies, which on the other hand absorb the effect of product offering which may be partly due to gasoline price changes. Therefore, our estimates mainly capture the effect of gasoline prices from the consumer side. The equilibrium effect from both the demand side and the supply side could be larger than our estimates for large price increases, especially in the long run. We are not aware of any study that addresses the important supply response, which is inherently a dynamic problem involving strategic considerations by auto makers.

Second, as we discussed previously, the changes in vehicle stock at the MSA level (or the state level, for that matter) can be attributed to vehicle scrappage and vehicle migration, which are not separately identified in the data. To the extent the majority of vehicle migrations occur across MSAs (within the country) and that these movements are correlated with variations in gasoline prices, the applicability of the estimates from the MSA-level data to national policy analysis may be hindered. To deal with this issue, we focus on old vehicles with the assumption that the migration of these old vehicles is mainly due to the relocation of the owners (rather than resale across MSAs) and is less likely to be correlated with changes in gasoline prices. This assumption, if too strong, may bias upward the estimates of fuel economy response for used vehicles. Although national-level registration data do not suffer this complication from vehicle migrations (e.g., exports to other countries), the identification of fleet fuel economy responses has to rely on only time-series variation in gasoline price, which compromises their ability to control for temporal unobservables.

6. CONCLUSIONS

The fleet fuel economy in the U.S. is the lowest among the industrialized nations and is falling further behind. In 2002, the average fuel economy of the vehicle fleet in the U.S. was about 13 MPG below that of countries in the European Union and 21 MPG below that of Japan. With volatile gasoline prices and growing concern about global climate change and local air quality, political support for curbing U.S. fuel consumption has increased dramatically in recent years. In this paper, we address a central question in the analysis of different policy alternatives by quantifying the response of fleet fuel economy to gasoline prices.

Taking advantage of a rich data set of all registered passenger vehicles in twenty MSAs, we are able to decompose the effects of gasoline prices on the evolution of the vehicle fleet into changes arising from the inflow of new vehicles and the outflow of used vehicles. We find that gasoline prices have statistically significant effects on both channels, but that their combined effect results in only modest impacts on fleet fuel economy. The short-run and long-run elasticities of fleet fuel economy with respect to gasoline prices are estimated at 0.022 and 0.204 in 2005. Our results suggest that the $4 per gallon gasoline prices observed in 2008 could result in a sizable increase in fleet fuel economy (i.e., an increase in average fleet MPG of 3.27, or 14% relative to 2001) and a large accompanying reduction in gasoline consumption if they were to remain permanent. Recall that record-high gasoline prices in 1970's only led to short-lived increases in fleet fuel economy and failed to induce any long-term solution such as fuel-saving technology innovations in the industry. In our view, recent high gasoline prices present opportunities for the development and diffusion of fuel-saving technological advances in the forms of favorable consumer sentiment and political environment, which could not be achieved through politically feasible gasoline tax increases.

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Table 1: Characteristics of the Twenty MSAs in 2000

MSA	Census Region	Median Household Income	Total Population ('000)	Average Household Size	Snow Depth ('inch)	Annual Gas Price	New Vehicle MPG	Fleet MPG	Fleet Age
Albany, NY	1	44,761	843	2.41	77.1	1.68	23.35	24.28	8.94
Atlanta, GA	2	50,237	4,037	2.69	3.1	1.33	22.16	23.12	8.04
Cleveland, OH	3	40,426	2,883	2.49	78.1	1.56	23.28	23.89	8.21
Denver, CO	4	50,997	2,080	2.54	56.7	1.59	22.31	23.35	8.52
Des Moines, IA	5	44,088	439	2.47	49.3	1.52	22.12	23.30	9.35
Hartford, CT	6	50,481	1,136	2.51	74.9	1.66	23.48	24.27	9.40
Houston, TX	7	42,372	4,105	2.87	0	1.5	21.77	22.68	7.78
Lancaster, PA	1	43,425	456	2.65	28	1.58	23.01	24.08	9.14
Las Vegas, NV	4	42,822	1,356	2.63	0	1.8	22.65	23.40	8.68
Madison, WI	3	46,774	411	2.37	52.2	1.6	22.93	23.96	8.89
Miami, FL	2	37,500	3,810	2.71	0	1.52	23.33	24.25	8.39
Milwaukee, WI	3	45,602	1,468	2.5	59.3	1.6	23.19	23.97	8.39
Nashville, TN	8	42,271	1,196	2.51	8	1.49	22.24	23.39	9.15
Phoenix, AZ	4	42,760	3,027	2.66	0	1.58	22.35	23.32	8.02
Saint Louis, MO	5	42,775	2,551	2.54	18.6	1.42	22.67	23.49	8.63
San Antonio, TX	7	38,172	1,554	2.79	0	1.48	21.91	22.77	8.42
San Diego, CA	9	47,236	2,717	2.72	0	1.77	23.01	24.09	9.02
San Francisco, CA	9	62,746	6,882	2.72	0	1.93	23.33	24.09	9.15
Seattle, WA	9	52,575	2,379	2.48	7	1.68	23.05	24.00	9.45
Syracuse, NY	1	39,869	705	2.53	191.9	1.68	22.78	23.82	8.81
Average		47,291		2.65		1.72	22.74	23.67	8.62
U.S.		41,486		2.61		1.46	22.30	23.62	8.68

Note: The average MSA demographics are taken from the US Census (www.ipums.org) and are weighted by the total number of households in the MSA. The average gasoline prices are weighted by the total number of registrations and the average MPGs are weighted by the number of registrations of each vehicle model. Both the household income and the gasoline price are in 2005 dollars. Fleet MPG and fleet age are the average MPG and vehicle age of all vehicles in year 2001.

Table 2: New Vehicle Regression Results

	(1)		(2)		(3)		(4)	
Variable	θ	**S. E.**	θ	**S. E.**	θ	**S. E.**	θ	**S. E.**
Constant	**22.026**	3.379	**6.368**	2.954	**16.516**	2.873	**18.016**	2.851
Log(N_{t-1})	**0.068**	0.006	**0.638**	0.024	**0.074**	0.007	**0.071**	0.007
GasPrice	**1.145**	0.211	**0.723**	0.133	**0.662**	0.128	**1.135**	0.169
Dollar Per Mile = GasPrice * GPM	**-26.700**	3.336	**-8.798**	2.735	**-15.842**	2.631	**-26.549**	3.185
GPM	**-203.280**	65.856	-46.249	61.647	**-171.780**	59.376	**-199.502**	58.905
Log(MHI)*GPM	9.546	8.215	4.013	8.026	2.387	7.373	9.470	7.377
Log(POP)*GPM	-0.621	1.417	-0.719	1.405	-1.078	1.283	-0.623	1.270
Log(AHS)*GPM	**63.623**	25.973	35.344	26.133	**57.355**	23.134	**63.384**	22.940
Snow * GPM	-0.057	0.034	-0.012	0.034	**-0.066**	0.031	**-0.056**	0.031
Log(MHI)	**-0.879**	0.420	-0.515	0.383	-0.178	0.356	-0.502	0.356
Log(POP)	**1.020**	0.072	**0.399**	0.073	**1.044**	0.061	**1.027**	0.060
Log(AHS)	**-5.255**	1.345	**-2.025**	1.232	**-3.400**	1.096	**-3.681**	1.082
Snow depth	0.002	0.002	0.000	0.002	0.003	0.002	0.003	0.002
Cell dummies (67)	Yes		No		Yes		Yes	
Year dummies (6)	Yes		No		No		Yes	
Year * class dummies (3)	Yes		No		No		Yes	
Region dummies (8)	Yes		No		No		No	
Adjusted R^2	0.619		0.516		0.606		0.613	
Durbin-Watson statistics	2.156		1.901		2.076		2.116	

Notes: Bold type indicates the coefficient estimate is statistically significant at the 5% level. The total number of observations is 6,578. The dependent variable in the equation is the logarithm of the total number of vehicles in a given MPG cell, Log(N_t). GPM, measuring fuel intensity, is the average gallon per mile of vehicles in the MPG cell. MHI is the median household income in $10,000 in the MSA; POP is the total population in millions the MSA; AHS is the average household size. These 3 demographic variables are from 2000 census. Snow is the average snow fall in inches from 1999 to 2005 in the MSA.

Table 3: Used Vehicle Survival Regression Results

	(1)		(2)		(3)		(4)		(5)	
Variable	β	**S. E.**	β	**S. E.**	β	**S. E.**	β	**S. E.**	β	**S. E.**
Constant	**-2.324**	0.718	-0.181	0.666	-0.232	0.659	**-2.314**	0.702	**-3.050**	0.682
GasPrice	**0.639**	0.128	**0.254**	0.100	**1.148**	0.112	**0.631**	0.158	**0.794**	0.128
DPM = GasPrice* GPM	**-18.362**	2.580	**-20.578**	2.134	**-18.807**	2.467	**-18.362**	3.164	**-19.293**	2.696
GPM	**126.766**	15.426	**150.910**	14.414	**144.393**	15.361	**126.767**	13.336	**136.751**	14.068
Age	**-0.644**	0.012	**-0.616**	0.013	**-0.640**	0.011	**-0.607**	0.022	**-0.536**	0.016
Age^2	**0.017**	0.000	**0.016**	0.000	**0.017**	0.000	**0.014**	0.001	**0.015**	0.001
Vintage before 1981	-0.027	0.043	**0.073**	0.026	-0.005	0.041	0.023	0.045	-0.071	0.039
Vintage 1981 - 1985	**-0.055**	0.022	**-0.101**	0.017	**-0.084**	0.021	**-0.124**	0.022	**-0.171**	0.021
Log(MHI)*GPM	**-20.306**	4.124	**-16.843**	3.363	**-18.797**	3.915	**-20.306**	3.885	**-20.008**	3.827
Log(POP)*GPM	**2.393**	0.814	**3.098**	0.708	**2.810**	0.803	**2.393**	0.732	**2.867**	0.788
Log(AHS)*GPM	**-64.068**	12.421	**-91.496**	12.368	**-84.383**	12.911	**-64.068**	10.379	**-74.230**	11.496
Snow*GPM	0.022	0.018	0.007	0.015	0.016	0.017	0.025	0.015	**0.034**	0.016
Log(MHI)	**1.485**	0.188	**1.742**	0.152	**1.065**	0.167	**1.487**	0.181	**1.727**	0.176
Log(POP)	**-0.232**	0.035	**-0.140**	0.031	**-0.226**	0.033	**-0.239**	0.032	**-0.229**	0.034
Log(AHS)	**6.309**	0.591	**4.538**	0.553	**3.647**	0.543	**6.319**	0.526	**5.487**	0.573
Snow	0.000	0.001	0.001	0.001	-0.001	0.001	**-0.003**	0.001	**-0.003**	0.001
Segment dummies (21)	Yes		Yes		Yes		Yes		Yes	
Make dummies (15)	Yes		Yes		Yes		Yes		Yes	
Segment dummies * age (21)	Yes		Yes		Yes		Yes		Yes	
Make dummies * age (15)	Yes		Yes		Yes		Yes		Yes	
Year dummies (7)	Yes		No		Yes		Yes		Yes	
Year * class dummies (3)	Yes		No		Yes		Yes		Yes	
Region dummies (8)	Yes		No		No		Yes		Yes	
ρ	**-0.169**	0.068	**-0.210**	0.073	**-0.175**	0.073			**-0.224**	0.116

Notes: Bold type indicates the parameter estimate is significant at the 5% level. Specifications 1-4 are based on vehicles older than 10 years, while specification 5 focuses on vehicles older than 15 years. Specification 4 uses only the first set of moment conditions.

Table 4: Survival Elasticity with Respect to the Gasoline Price in 2000

Model	MSA	MPG	Gas Price	Survival Prob.	Survival Elasticity
Panel 1: Based on Estimation Results from Specification (1)					
Older than 10 years	All 20	24.43	1.68	0.890	-0.023 [-0.042 0.001]
1985 Honda Civic	Houston	39.70	1.58	0.801	0.051 [0.001 0.090]
1985 Chevy Impala	Houston	21.18	1.58	0.885	-0.038 [-0.059 -0.014]
1985 Honda Civic	San Francisco	39.70	2.04	0.874	0.045 [0.009 0.091]
1985 Chevy Impala	San Francisco	21.18	2.04	0.782	-0.100 [-0.152 -0.045]
Panel 1: Based on Estimation Results from Specification (5)					
Older than 15 years	All 20	24.37	1.60	0.779	-0.014 [-0.035 0.013]
1985 Honda Civic	Houston	39.70	1.58	0.801	0.089 [0.054 0.143]
1985 Chevy Impala	Houston	21.18	1.58	0.885	-0.020 [-0.042 0.000]
1985 Honda Civic	San Francisco	39.70	2.04	0.874	0.078 [0.045 0.125]
1985 Chevy Impala	San Francisco	21.18	2.04	0.782	-0.052 [-0.105 -0.002]

Note: The results in the first row in both panels are weighted averages where the weight is the total registrations of the vehicle model. The numbers in the brackets in the last column define the 95% confidence interval from parametric bootstrapping.

Table 5: Fleet Fuel Economy in 2005 under Tax Alternatives

Tax Alternatives	New Vehicles			Used Vehicles			All vehicles		
Current Tax	23.67			23.65			23.65		
Panel 1: Tax Increase from 2005									
	Increase in Average MPG in 2005								
+ $0.25	0.48	[0.37	0.59]	0.02	[0.00	0.04]	0.06	[0.03	0.08]
+ $0.60	1.14	[0.88	1.41]	0.04	[0.02	0.07]	0.13	[0.09	0.17]
+ $1.00	1.88	[1.46	2.34]	0.07	[0.04	0.11]	0.22	[0.17	0.32]
+ $2.40	4.53	[3.48	5.70]	0.18	[0.12	0.23]	0.59	[0.36	1.06]
Elasticity of Average MPG	0.191	[0.150	0.235]	0.006	[0.000	0.015]	**0.022**	**[0.013**	**0.031]**
Panel 1: Tax Increase from 2001									
	Increase in Average MPG in 2005								
+ $0.25	0.51	[0.38	0.61]	0.24	[0.18	0.28]	0.26	[0.19	0.30]
+ $0.60	1.22	[0.91	1.44]	0.54	[0.40	0.62]	0.59	[0.45	0.69]
+ $1.00	2.02	[1.51	2.40]	0.86	[0.72	1.05]	0.96	[0.77	1.19]
+ $2.40	4.87	[3.60	5.85]	1.95	[1.51	2.62]	2.23	[1.71	3.06]
Elasticity of Average MPG	**0.204**	**[0.148**	**0.259]**	0.093	[0.069	0.110]	0.101	[0.077	0.119]

Notes: The numbers in the table are from simulations based on regression results for new vehicles and used vehicles. The numbers in brackets define the 95% confidence interval from parametric bootstrapping.

Table 6: Heterogeneity in the Elasticity of Fleet Fuel Economy from 1999 to 2005 in 20 MSAs

Panel 1: Summary Statistics of the Elasticities

Elasticity of Fuel Economy	**Mean**	**S. D.**	**Min**	**Max**
All Vehicles	0.014	0.013	0.003	0.036
New Vehicles	0.148	0.134	0.080	0.293

Panel 2: The Response of the Elasticities to the Gasoline Price and other Demographics

	All Vehicles				**New Vehicles**			
	(1)		**(2)**		**(3)**		**(4)**	
Variable	**Para.**	**S. E.**	**Para.**	**S. E.**	**Para.**	**S. E.**	**Para.**	**S. E.**
Constant	**-5.396**	0.462	**-7.303**	0.454	**-3.485**	0.206	**-3.898**	0.267
Log(GasPrice)	**0.687**	0.174	**0.870**	0.162	**0.869**	0.074	**0.792**	0.076
Log(MHI)	-0.101	0.111	0.112	0.133	**0.205**	0.060	0.114	0.075
Log(POP)	**0.043**	0.017	0.036	0.024	**-0.038**	0.010	**-0.033**	0.013
Log(AHS)	-0.258	0.402	**1.461**	0.381	**0.482**	0.173	**1.218**	0.216
Snow depth	-3.3E-04	3.5E-04	**-1.1E-03**	3.3E-04	-1.3E-04	2.4E-04	**-1.3E-03**	2.6E-04
Year dummies (6)	Yes		Yes		Yes		Yes	
Region dummies (8)	Yes		No		Yes		No	
Number of observations	140		140		140		140	
Adjusted R2	0.973		0.947		0.973		0.942	

Notes: The summary statistics are for the elasticity estimates for each MSA in each year from 1999 to 2005. They are weighted by the total number of vehicle registrations in the MSA. The dependent variable in panel 2 is the logarithm of the elasticities. Bold type indicates the parameter estimate is significant at the 5% confidence level. The standard errors are heteroskedasticity-robust. We also estimate (1) and (3) in the linear-linear form, which gives qualitatively the same results. The R^2s are 0.946 and 0.938, respectively.

Table 7: Alternative Specifications on the Response of New Vehicle Fuel Economy to Gasoline Prices

	(1)		**(2)**		**(3)**		**(4)**	
Variable	**Para. (1)**	**S. E. (2)**	**Para. (3)**	**S. E. (4)**	**Para. (5)**	**S. E. (6)**	**Para. (7)**	**S. E. (8)**
Constant	3.476	0.078	3.530	0.048	3.479	0.049	31.096	1.764
GasPrice	0.075	0.017	0.050	0.004	0.106	0.008	1.637	0.392
MHI	-0.016	0.003	-0.009	0.002	-0.014	0.002	-0.349	0.077
POP	0.007	0.002	0.010	0.001	0.007	0.001	0.164	0.040
AHS	-0.150	0.027	-0.196	0.017	-0.189	0.017	-3.320	0.609
Snow depth	-0.033	0.012	0.008	0.006	0.006	0.006	-0.817	0.269
Year dummies (6)	Yes		No		Yes		Yes	
Region dummies (8)	Yes		No		No		Yes	
Number of observations	42949		42949		42949		42949	
Adjusted R^2	0.146		0.142		0.144		0.136	
Implied Elasticity	**0.143**		**0.095**		**0.201**		**0.136**	

Notes: Bold type indicates that the parameter estimate is statistically significant at the 95% level. The dependent variable in the first three regressions is the logarithm of MPG of a new vehicle model while that in the last regression is just the MPG. The regressions are estimated using weighted OLS where the weight is the total number of registration of each vehicle model. Robust standard errors are reported. The implied elasticity is the elasticity of new vehicle MPG with respect to gasoline prices. The implied elasticity for the last regression is evaluated at the weighted average gasoline price ($1.90) and the weighted average MPG (22.89) from 1999 to 2005 in the 20 MSAs.

Figure 1: Gasoline Prices in Selected MSAs 1997-2005

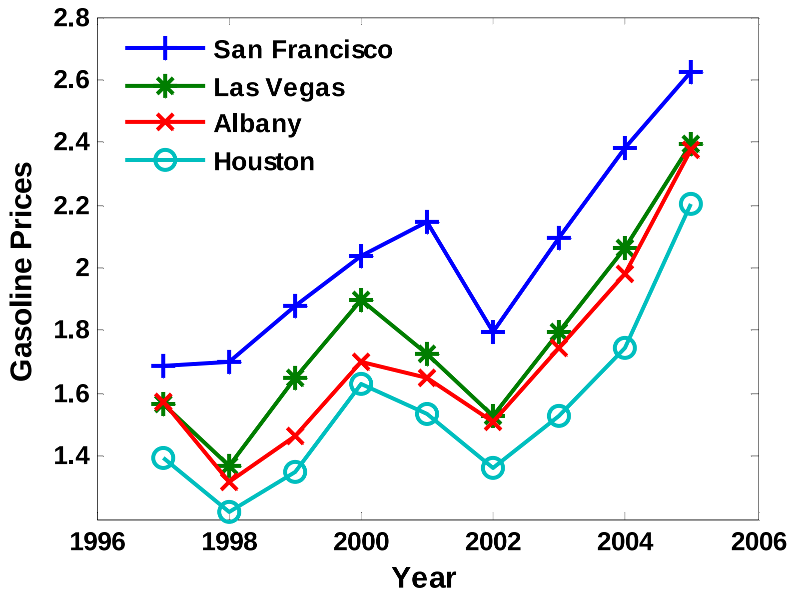

Figure 2: Fuel Economy Distributions