AN ANALYSIS OF INCOME DISTRIBUTION EFFECTS OF A GASOLINE TAX: EVIDENCE FROM THE U.S. MICRO-LEVEL DATA

A Dissertation
presented to
the Faculty of the Graduate School
at the University of Missouri-Columbia

In Partial Fulfillment
of the Requirements for the Degree

Doctor of Philosophy

By

HYUNG-GUN KIM

Dr. Saku Aura, Dissertation Supervisor

MAY 2007

The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

AN ANALYSIS OF INCOME DISTRIBUTION EFFECTS OF A GASOLINE TAX: EVIDENCE FROM THE U.S. MICRO-LEVEL DATA

presented by Hyung-Gun Kim,

a candidate for the degree of doctor of philosophy of Economics,

and hereby certify that, in their opinion, it is worthy of acceptance.

Professor Saku Aura

Professor Ronald A. Ratti

Professor Shawn Ni

Professor Jeffrey Milyo

Professor Doh C. Shin

This dissertation is dedicated to my loving family.

ACKNOWLEDGEMENTS

I would like to acknowledge many people who have provided support during my doctoral work. I would never have been able to finish my dissertation without their help and support. First, I would sincerely like to thank my advisor, Dr. Saku Aura, for his excellent guidance, advice, considerations, and especially for patiently providing me with strong economic background necessary to complete this dissertation. He has been a supportive advisor and a trusted mentor during my doctoral years. I also would like to thank all the members of my committee, Dr. Ronald A. Ratti, Dr. Shawn Ni, Dr. Jeffrey Milyo, and Dr. Doh C. Shin who have given their valuable time and advice. Their suggestions and careful reviews have greatly improved this dissertation.

I also have been fortunate to have good colleagues, staff and friends. I would like to thank Dr. Hojong Kang, Mr. MyoungWoon Kim, Mr. JungWook Park, Mr. ByungNae Yang, Mr. Sunglyong Lee, Mr. Youn Seol, and Mr. Muhammad Khan. They always have been willing to give me their best suggestions. It would have been a lonely and drudge computing lab without them, where I have been mostly working for my dissertation. I would like to thank Ms. Lynne Riddell for great support. I would also like to thank my good friends, Mr. SungSoo Kim and Mr. Peter Holowaty.

Finally, I would especially like to thank my family. My father has motivated and encouraged me to continue my doctoral work at the most frustrating moments. My mother has been an endless source of love and support. I am also grateful to my sister, brother-in-law, niece, and my brother for their sacrifice and encouragements.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS ii

LIST OF ILLUSTRATIONS v

ABSTRACT vi

1. Introduction 1

2. Literature Review 4

2.1 Price Elasticity of Gasoline Demand 4

2.1.1 Aggregate Analysis 5

2.1.2 Disaggregate Analysis 6

2.2 Distribution Effects 10

2.3 Public Transportation 14

2.4 The Purposes of Driving (Work/Leisure) 18

3. The Model 22

4. Data and Summary Statistics 29

4.1 Data Description 29

4.1.1 Household Characteristics 29

4.1.2 Vehicle Attributes 31

4.1.3 Residential Areas 32

4.2 Vehicle Choice Portfolios and Main Variables 34

4.2.1 Vehicle Portfolios 34

4.2.2 Main Variables 36

4.3 Summary Statistics 39

5. Empirical Results 45

5.1 Vehicle Portfolio Choice Model....45
5.2 Vehicle Miles Traveled Demand Model....49
5.3 Short-Run Price Elasticity of Gasoline Demand....52
5.4 Distributional Effects....56
6. Conclusion....60
REFERENCES....63
APPENDIX....67
1. Data....67
2. Estimation Results....71
VITA....75

LIST OF ILLUSTRATIONS

Table Page

1: Fitted Model for Used Car Price and Depreciation Rate 37

2: Fitted Model for Typical Miles 38

3: Household Characteristics and Vehicle Attributes by Number of Vehicles 40

4: Household Characteristics and Vehicle Attributes by Vehicle Types 41

5: Household Characteristics and Vehicle Attributes by Vehicle Vintages 42

6: Average Demand for VMT by Household Characteristics.....................................44

7: Summary Results for Household Vehicle Choice Model.......................................46

8: Chow Test Results 50

9: Results from VMT Demand Model 51

10: Elasticity 53

11: Tax Burdens...57

A1: Vehicle Choice Structure and Average of Main Variables..................................68

A2: Total Public Transportation Annual Service Miles Drive 69

A3: Definitions of Variables in Nested Logit Model..71

A4: Full Results of Vehicle Choice Model 72

Figure Page

A1: U.S Regular Conventional Retail Gasoline Prices (03/2001- 05/2002) 67

A2: Average MPG for Sedans and SUVs...67

AN ANALYSIS OF INCOME DISTRIBUTION EFFECTS OF A GASOLINE TAX: EVIDENCE FROM THE U.S. MICRO-LEVEL DATA

Hyung-Gun Kim

Dr. Saku Aura, Dissertation Supervisor

ABSTRACT

This is a study of an income distributional effect of a gasoline tax, taking account of behavioral responses of households depending on income levels. We examine the price elasticities of gasoline demand and the tax burdens within income groups based on different transit services in residential areas. Empirical analyses are presented, adopting the Dubin-McFadden correction method, with the primary data drawn from the 2001 National Household Travel Survey. We find that households show different responses to higher price of gasoline based on their income and residential areas. In particular, households living in areas that have greater transit supply than the U.S. average show the responses that tend to enhance the regressivity of a gasoline tax.

1. Introduction

World oil prices have been moving up steadily since 2000 and it is likely that a stable period of high oil prices has set in. In spite of this higher level, the United States still shows an overwhelmingly higher rate of gasoline consumption compared to any other country. In 2003, Americans consumed almost 9 million barrels of gasoline per day, which accounted for more than 40 percent of total gasoline consumption of the world.[1] This high level of gasoline consumption, coupled with sustained higher world oil prices, naturally raises the issue of a gasoline tax as a policy to control demand.

In order to implement the most effective gasoline tax, it is essential to understand the response of a household to a higher gasoline tax. This response can be examined by a gasoline demand model, which has been broadly studied since the 1970's. Gasoline demand studies have used various economic models with different types of data to examine the price elasticity of gasoline demand. The robust empirical evidences from these studies generally conclude that gasoline demand is relatively price inelastic. These results can be used to analyze the optimal level of a gasoline tax by simulating the change of households' gasoline consumption in a new gasoline tax policy.

A good tax policy, however, should not only consider an efficiency problem, but also an equity problem. To this end, very few studies have employed the price elasticity of gasoline demand to analyze the distributional effects of a gasoline tax on income. A gasoline tax has been simply considered regressive since the income elasticity is smaller

[1] Source: Energy Information Association (EIA)
"http://www.eia.doe.gov/emeu/international/oilconsumption.html"
Gasoline consumption for the world total was about 20 million of barrels per day in 2003.

than one. This is usually estimated with price elasticities in gasoline demand studies. However, income elasticity studies have certain limitations. One problem is that they do not actually show the different financial burdens of the gasoline tax by income groups; the other problem is that such studies include vehicle owners only.

Poterba (1991) recognizes the weaknesses of the conventional studies and suggests an alternative approach using 1985 Consumer Expenditure Survey (CES). His descriptive study includes households without cars and computes the average gasoline expenditure as a share of annual household expenditure within each income decile. He then shows that the gasoline tax is much less regressive than previous studies have estimated between the lowest income level households and middle-income households. West (2004) develops the analysis further, allowing the response of the household to the change of gasoline price within each income group, and thus assigning different price elasticities to each income level. Using 1997 CES data, the study shows that the highest price elasticity of gasoline demand is in the lowest income level and it decreases as the income levels increase, except in the highest brackets. Due to these different households' responses, West (2004) concludes that, the gasoline tax is more progressive between the low and middle-income distributions, and less regressive between middle and high-income distributions.

These results are encouraging for research in public transportation because a convenient public transit network can be a substitute for private driving. At the same time, poor households are more likely to make use of public transit, as they cannot afford to buy or to fuel their vehicles. This travel behavior among poor households is pointed out by Poterba (1991) and West (2004), and they both suggest that the distribution of the public transportation usage is closely related with the income distribution effect of the gasoline tax. Nevertheless, the short-run effect of public transportation as a substitute for private driving for households is ambiguous. West (2004) perceives that the effect of public transit as a substitute of private driving is greater on poorer households while Kayser (2000) suggests that its effect is greater on the richer households.

A further investigation on the distributional effects of a gasoline tax is required, considering the accessibility (or lack thereof) of public transportation. This study examines the different households' responses to the gasoline price change, within different income levels, based on their residential areas, which are classified by public transit supply. Toward the end, the responses are used to analyze the income distributional effects of a gasoline tax.

The rest of paper is organized as follows. In the second section, the previous studies on specific topics of gasoline demand, distributional effects of a gasoline tax, public transportation, and purposes of driving (work/leisure), which are closely related to our study, are reviewed. Section 3 then presents models of both household vehicle choice and Vehicle Miles Traveled (*VMT*) demand. In section 4, the data, main variables and the nested structure of the vehicle choice model are briefly described. In section 5, empirical results are reported and interpreted. Section 5 concludes.

2. Literature Review

The effects of gasoline tax on three specific topics – distribution, use of automobiles and public transportation – are closely related to our study. Therefore, reviewing previous literature that explores these three topics is needed to develop our research. In addition, econometric models of gasoline demand studies are first reviewed separately because various effects and interactions of all these topics are reflected in households' demand elasticities. To adopt and develop the best suitable model structure, it is important to understand how the structures of the gasoline elasticity studies have been developed.

2.1 Price Elasticity of Gasoline Demand

There has been a large body of literature on price elasticity of gasoline demand for a long time. Various econometric tools have been used, and different types of data have been employed. It is not necessary to cover all of these studies for the purpose of this review. Instead, the review on this topic mostly relies on literature surveys to see the big picture of gasoline demand studies, with the structure of models being the central topic. [2] Gasoline demand studies are classified into two groups according to data and model types. One is aggregate analysis, and the other is disaggregate analysis. In this way, it is easier to explain our approach.

[2] There is well-explained survey literature. See Dahn and Sterner (1991a), Dahn and Sterner (1991b), Dahl (1995), Espey (1996), Graham and Glaister (2002), and Harrington and McConnell (2003).

2.1.1 Aggregate Analysis

Classical aggregate models on gasoline demand are described well by Dahl and Sterner (1991a, 1991b). They review literature on almost one hundred econometric studies of gasoline demand elasticities, which were mostly used in 1980s. The reviewed econometric models have more than 300 estimated demand equations and most models have the basic structure of aggregate analysis, which have gasoline demand as a function of the real price of gasoline and real income. Therefore, we can investigate both price and income elasticities from the estimated parameters. This simple structure including gasoline demand, price, and income is maintained in every other aggregate study as well (Harrington and McConnell, 2003).

It is difficult, however, with this simple static model to capture the dynamic behaviors such as long-run elasticities (Dahl and Sterner, 1991b). Thus, studies that adjust long-run reactions include variables other than price and income. One modified structure has lagged variables. For example, the most frequently used lagged structure model has the quantity of gasoline demanded last period as an explanatory variable, so that it can capture the possibility that how earlier income and price may affect today's consumption (Dahl and Sterner, 1991b). In addition, there are many other lagged structures relaxing the weight on price and income lags, or other variables. The other type of modified models includes vehicle-related variables such as vehicle stocks and characteristics to capture the long-run adjustment. Vehicle-related variables in these models capture long-run elasticities while income and price capture short-run elasticities (Dahl and Sterner, 1991b).

With these aggregate structures of models and data, the price and income elasticities of gasoline demand in the short-run and the long run at aggregate level can be examined, and the results can be used for aggregate level comparisons or other purposes at the aggregate level. However, this approach has limitations due to the nature of aggregate level data. Our interests in this research involve heterogeneous household behaviors contingent on their income and public transit system. Thus, aggregate approaches are not appropriate for our study.

2.1.2 Disaggregate Analysis

One advantage of using disaggregate level analysis is that, unlike aggregate level, it allows an examination for the various behaviors of different groups depending on households or vehicle characteristics. Early disaggregate studies, such as those in Archibald and Gillingham's (1980), and Greening et al.'s (1995), take this into consideration and estimate price and income elasticities as well as the effects of various groups of households and vehicle characteristics. Yet, they do not enjoy the full advantages of disaggregate level. The vehicle choices are treated as dummy variables in Archibald and Gillingham's (1980) and Greening et al. (1995) do not even consider individual vehicle choices. As a result, they fail to consider the importance of interrelation between individual vehicle choices and gasoline consumption.

The essential advantage of micro level studies is that the model can be explicitly derived from the well-built microeconomic theory of individual behavior, and in the case of the gasoline consumption model, it requires special treatment of the linkage between continuous gasoline use and discrete vehicle choice to be consistent with true microeconomic theory (Train, 1986). For example, households that buy small hybrid cars would have different unobserved characteristics than those that buy huge SUVs, and the unobserved household characteristics could be correlated with their vehicle miles traveled (*VMT*), which is the final consumption provided by gasoline. The households' choice of vehicles will then be endogenous with their use of vehicles. Thus, a gasoline demand study without a method to correct this self-selection problem will be inconsistent.

A consistent framework for the analysis of gasoline demand was originally built by Dubin and McFadden (1984). They derive the conditional expectation correction method to adjust the bias caused by the interrelated decisions between durable goods consumption and their use.[3] They then show that the ordinary least squares (OLS) without the correction could be biased. Our study adopts this framework as a main tool for consistent estimation to observe various behaviors with respect to gasoline price. More details are shown in a later section. In this section, a review of the several previous gasoline demand studies adopting Dubin and McFadden's framework will suffice.

Mannering and Winston (1985) apply the Dubin and McFadden's model to a dynamic analysis of household vehicle choice and use. They use three-period intertemporal utility maximization problem. With this dynamic structure, they estimate discrete vehicle choice, and jointly estimate price and income elasticities in both long run and short run, using the primary data drawn from the National Interim Energy Consumption Survey (NIECS) and Household Transportation Panel for the 1977 – 1980 periods. Their results on gasoline elasticities are small and decrease over time, so they

[3] Their application for the particular case was the demand for electrical appliances and the demand for electricity.

expect that the gasoline tax increase in 1982 may have a small effect on both vehicle use and efficient resource allocation. In addition, they emphasize that US households prefer domestic brands such as Ford and GM to foreign brands. It is captured by discrete choice estimation by making use of vehicle indicator variables.

Using cross-sectional data in the National Transportation Survey of 1978, Train (1986) provides an excellent example of how to treat the linkage between the demand for vehicles and their use.[4] He adopts the nested logit structure from McFadden (1978) to ensure the Independence of Irrelevant Alternatives (IIA) assumption holds. Thus, his model consists of several sub-models which, estimate vehicle quantity choices, class and vintage choice, the total annual *VMT* and the proportions of *VMT* by the different uses of vehicles. Each sub-model is estimated sequentially, and treatments for the interrelation between estimations are done through instrumental variables.[5] For example, vehicle class and vintage choice model includes the average operating cost of the chosen vehicle as an explanatory variable. Instead of using actual operating cost, the average operating cost is estimated with implied miles traveled, which is determined by household characteristics, and used in order to represent household *VMT* demand. In a similar way, a predicted operating cost, which is estimated with exogenous household characteristics, is applied in *VMT* demand model to avoid an endogeneity bias.

Both dynamic and cross-sectional studies above recognize the interrelation between the discrete vehicle choice and continuous use, and develop the appropriate model for their interests. Even if both developed models have a consistent structure to

[4] This study is shown in chapter 8 of the book.

[5] For this particular study using real data, the selectivity correction term derived by McFadden and Dubin (1984) is not adopted even if he describes it in chapter 5.

examine vehicle choice and use, they instead emphasize on details of vehicle choice more than the different reactions of various households for gasoline price variation. A more appropriate approach for our study is shown in more recent studies. Two recent studies are reviewed, that have developed structures more appropriate to our research.

Goldberg (1998) modifies Dubin and McFadden's model to study the effects of the Corporate Average Fuel Economy (CAFE) standards on automobile sales, prices, and fuel consumption. The research considers both supply and demand sides. The parameters in demand side are estimated by the modified framework using the Consumer Expenditure Survey (CES) from 1984 to 1990. Although the main purpose of the research is examining the effects of the CAFE, more household characteristics are taken into consideration in both discrete vehicle choice and continuous use estimations, compared to previous studies. For example, vehicle characteristics are interacted with household characteristics in the discrete vehicle choice model, and continuous use model has various household characteristics such as income group indicators and unemployment. These variables allow us to observe various reactions on the consumption side. This framework is developed further by West (2004) to study the various households' behaviors.

Based on Goldberg's framework, West (2004) adds an interaction term between income and the operating cost per mile into the continuous *VMT* decision model. Therefore, all different gasoline price elasticities are estimated depending on their income levels, and one can examine the distribution effects of gasoline tax from them. This approach of study can be applied to other types of household characteristics such as employment rate and public transportation access. Our research adopts this model, and includes interaction terms.

2.2 Distribution Effects

In general, the gasoline tax is considered regressive, although it may differ in magnitude depending on methodologies and use of the dataset. This traditional conclusion is based on two distribution study approaches.

One approach is that income elasticity is directly estimated accompanied with price elasticity in the gasoline demand model, because most gasoline-demand studies include both household income and gasoline price as explanatory variables. With this approach, the estimated result, an income elasticity of less than one, concludes that the gasoline tax is regressive. In addition, some of these studies include analyses of various price elasticities at different points of total income by splitting the sample based on income levels or by adding an income interaction term. It will be worth it to review these previous results on variations across their income levels as our study also considers various households behaviors when an additional gasoline tax is imposed, and their resulting impact on the income distribution.

One of the earliest reports studying income elasticity is shown in Archibald and Gillingham (1980). Their model includes total household consumption expenditure as a proxy for permanent income, and using 1972–73 CES, it estimates expenditure elasticities of less than one, 0.344 for one-vehicle households and 0.455 for more than one vehicle households. In addition, this study estimates different price elasticities of gasoline demands based on three levels of expenditure subgroups, which are split from the total sample, and shows that a lower expenditure subsample has more elastic price demand of gasoline.

Two similar studies recently reported small income elasticities as well. Using household data drawn from the Panel Study of Income Dynamic (PSID) for 1981, Kayser (2000) estimates short-run income elasticities of 0.48 for the gasoline demand model, and 0.49 for the miles traveled model by using two-stage Heckman selection correction.[6] The study also analyzes different price elasticities of gasoline demand by adding an interaction term between the price of gasoline and income. Contrary to the result from Archibald and Gillingham (1980), the estimated coefficient on the interaction term shows that a price elasticity of gasoline demand gets smaller as the household income increases. Kayser (2000) proposes, as a hypothetic reason for this surprising estimated result, that poorer households reserve larger portions of private driving for necessary purposes, as they do not have any alternative due to their limited budgets. On the other hand, richer households reserve more portions of private driving for leisure, and have more alternatives such as trains and airplanes available.

Sipe and Mendelsohn (2001) also estimate income elasticities between 0.1 and 0.2 by using an experimental survey conducted in Los Angeles, which has the lowest gasoline tax, and Connecticut, which has the highest gasoline tax.

However, this type of study simply estimates the gasoline demand changes with respect to the household income. They do not actually show the different financial burdens of the gasoline tax based on income groups. Another problematic weakness from the distribution point of view is that they only include households, which own

[6] As discussed earlier, the model considering the self-selection bias from vehicle choice give more confident results than the model without the correction.

vehicles. These weaknesses are well recognized by the alternative approach provided by Poterba (1991).

Poterba (1991) studies the distribution effects of the gasoline tax using 1985 CES data. This study categorizes the households into ten different deciles depending on their annual expenditure, then computes the average gasoline and motor oil expenditure as a share of annual household expenditure within each decile. An interesting finding from the study is that the lowest decile shows a lower gasoline expenditure ratio than middle expenditure deciles, which indicates that gasoline tax is not regressive between very low and middle expenditure households, while the rest of expenditure deciles from middle to high expenditure households show a regressivity. Poterba (1991) finds one of reasons in the heterogeneity within deciles; lower expenditure deciles contain more households with no gasoline expenditures as the lowest expenditure decile has 36.5% of households who do not have any gasoline expenditure while it is 0.7% for the fourth decile.[7] These households, which have no gasoline expenditure, would alleviate the regressivity between low and middle expenditure groups. It is likely that very low-income households in urban areas tend to use public transit more often than other income groups (Poterba, 1991). This finding suggests that the distribution studies of gasoline need to understand

[7] Poterba (1991) argues that annual expenditure is a better proxy to indicate the well-being of the household than annual income. The study shows the different results by comparing two proxies. Using annual income, results are more regressive. In fact, this is not only a matter of gasoline tax. Other taxes show similar results when viewed from a lifetime perspective. For example, Gasoline, alcohol, and tobacco taxes are analyzed by Poterba (1989), and vehicle registration fees and other emissions related fees are analylized by Walls and Hanson (1999). In addition, Caspersen and Metcalf (1994) show value added taxes would tend to be less regressive from a lifetime perspective. However, Casperson and Metcalf (1994) also note that their results using current consumption as a proxy tend to underestimate true regressivity, due to its extreme assumption on the degree of liquidity, as opposed to the assumption of annual income. In fact, although the fluctuating annual income does not exactly reflect the real well-being of the households, it is not reasonable either to assume that households sustain their consumption levels constant for their lifetime (Metcalf, 1997).

and reflect variations across income groups. It is reasonable to assume that each income group has a different response to the gasoline price changes. As discussed earlier, price elasticity in the gasoline consumption model can reflect the variations of households' responsiveness to the gasoline price. Therefore, both price elasticities within income groups and a descriptive study across income groups are both required to analyze more details of the distribution effects of a gasoline tax.

A study by West (2004) combines the study of price elasticity and descriptive study. Using 1997 CES, West (2004) estimates price elasticity within each expenditure group to analyze their different responses to a gasoline price. Assuming the optimal tax of 40 cents higher price per gallon of gasoline, she then computes the expected gasoline tax paid and consumer surplus loss as a percentage of total expenditure of household for each expenditure group. The study provides two estimated results: one for all households, and the other for vehicle owners. The result for vehicle owners shows that gasoline tax is regressive over all expenditure deciles. On the other hand, the result for all households shows that gasoline tax is progressive from the lowest to middle expenditure households while it is regressive from the middle to the highest expenditure households, just like Poterba's (1991) results. In addition, the study finds that the demand for *VMT* is more elastic as households become poorer, except for the two highest expenditure deciles. According to West (2004), this result enhances the progressivity of gasoline tax from the poor to the middle class while it alleviates regressivity from the middle class to the rich.

2.3 Public Transportation

The supply of public transportation must be another significant effect on vehicle ownership, miles driven, and thereby on income distribution as well. In particular, a faster and more convenient public transit network could be a good substitute for private vehicle miles driven, and would cause the price responsiveness of households to become more elastic.

Nevertheless, few studies investigate the effect of transit supply on price elasticity. Instead, most gasoline-demand studies examine the effect of transit on the gasoline demand or *VMT*. Besides, they often treat the quality of transit as an indicator variable. Goldberg (1998) uses a dummy variable, “bigcity” that is defined as the city with more population than a 1.25 million. West (2004) has a dummy of metropolitan area that has more than 4 million population. Kayser (2000) sets two dummy variables based on Metropolitan Statistical Areas (MSA) and rural area.[8] These studies capture the effect of transit on vehicle decisions, and gasoline demand in the intercept of the models. The results are mixed. Goldberg (1998) and Kayser (2000) find that households would drive less in the larger population areas, while West (2004) finds that households would drive more in larger population areas.[9] Sometimes, a gasoline demand study uses some measures of transit supply as proxies. Train (1986) uses both a dummy variable, urban with more than one million populations, and a proxy, the number of transit trips taken per capita in the household’s residential area, to measure the quality of transit for each household. The study finds that the quality of a transit system decreases the probability

[8] MSA is a Census classification for an urbanized area where it has a population of more than 50,000.

[9] OLS result has a positive coefficient, while IV result, which is more reliable, shows a negative result.

for households to own more vehicles and decreases annual vehicle miles, and the dummy variable indicates households would drive more in an urban area with more than one million populations.

In short, it is very difficult to measure the supply of public transportation and show its effects on a gasoline demand model. All these dummies and a proxy, population size and the number of transit trips are not likely to reflect the accessibility of public transportation successfully in the gasoline demand model. For population dummies, there is no clear evidence for a positive relationship between the population size of a residential area and the supply of public transportation. Instead, they contain many other unobserved factors, such as congestion of traffic and the quality of highway networks, than the supply of public transit. Furthermore, the studies using these dummies overlook the higher cost of living in metropolitan areas with higher population. That should be properly taken into account since the price level can affect both household's real income and real gasoline price. A more specific variable, the number of transit trips, faces another problem as well. This variable could cause an endogeneity problem because households, who tend to use public transportation more often, are likely to locate in places where they have better access to the stations (Bento at al., 2003).

A better measurement of public transit supply in the gasoline demand model is provided by Bento et al. (2003). They develop the measurements for both the citywide transit network supply and the accessibility of transit to peoples' homes. For whole area, they employ total bus route miles and total rail route miles, supplied per square kilometer. For accessibility to homes, they estimate the instrumented distance to local transit to avoid the possible endogenous problem. This instrument is estimated from a regression of the distance to the transit stop (dependent variable) on the average percent of workers who commute by public transit (independent variable) in a set of affordable census track. They identify this census tracks as affordable if the median income in the track from 1990 census data is lower or equal to the household income from their main data, 1990 National Personal Transportation Survey.[10] Using these variables, the study concludes that better accessibility of transit decreases the probability of owning vehicles, and decreases the average annual *VMT*. The results are modest, but significant.

For all that, as mentioned earlier, the effects of public transit supply on price elasticity are out of focus in the gasoline demand studies. Studies have only concerned themselves with the effects on gasoline demand. A higher gasoline price is one of the important factors which encourages households to substitute more to public transit from private driving (Baum-Snow and Kahn, 2000), and conversely, the existence of better accessibility to public transit in the zone of households' lives would have an effect on their price elasticities.[11] Furthermore, the rates of response due to the higher gas price, depending on the existence of public transit must be sorted by income groups as well. For example, with the U.S. Census micro data for 1980 and 1990, Baum-Snow and Kahn (2000) study the effects of new rail trails by comparing from before the renovation of transit system and after in five US cities where the rail systems were upgraded. They demonstrate that new transit rail systems significantly influenced a few households to switch from private driving to public transit. Some demographic groups are more

---

[10] See Bento at al. (2003) for more details.

[11] There are other important factors; the urban form or density, road density, other costs related to private driving such as parking fees.

influenced than other groups.[12] Therefore, we need to take the supply of public transit into consideration when we study the effects of gasoline tax on distribution. To our knowledge, none of the gasoline tax studies has gone into these details yet.

Greening at al. (1995) investigate different price elasticities of both gasoline demand and vehicle miles traveled not based on public transit supply, but instead, based on four census urban regions and rural areas. In this study, the total national sample drawn from 1990 CES is split into Northeast, Midwest, South, West urban, and total rural areas in order to estimate the different households' responses based on regions. Therefore, by comparing elasticities in urban areas and in rural areas, we may get information on the relationship between public transit supply and price elasticity of gasoline demand.

Households in each area, Northeast, Midwest, South, West urban, and rural areas show the estimated price elasticities of, respectively, -0.245, -0.234, -0.407, -0.292, and -0.341 in terms of vehicle miles traveled, and all price elasticities are significant at 1% level. The results, surprisingly, imply that households in urban areas who face more alternatives to private driving are less sensitive to gasoline price changes than households in rural areas who are assumed to face less public transit supply, except in South urban. Besides, price elasticity for households in Northeast urban areas is second lowest among those in four urban areas even although Northeast urban includes well-known cities for the most developed public transit system in the US such as New York and Boston.

These results, therefore, suggest that the effect of public transit supply as a substitute for private driving on the short-run price elasticity of gasoline demand can be

[12] non-blacks and people over age 35 are most influenced by the renovation of the public rail transit, because these renovations on rail transit in five US cities are done mostly the suburbs.

very different from what people generally expect – households who face more public transit supply are more sensitive to the gasoline price changes.

2.4 The Purposes of Driving (Work/Leisure)

For an efficient gasoline tax policy, it is important to recognize gas tax as a Pigovian tax to offset the negative externalities such as pollution and traffic congestion, but at the same time, it is also important not to forget that gasoline tax is one of most important commodity taxes. In other words, all seminal theories in commodity literatures, such as those by Ramsey (1927), and Corette and Hague (1953-54), should be considered, accompanied with the corrective tax for studying gasoline tax policy. The Ramsey rule suggests a higher tax on relatively inelastic goods to minimize the social cost in a second-best world. Gasoline consumption is one of these cases as it is generally accepted that the elasticity is less than one. In fact, this is one of the important theoretical grounds for the British government to impose a high rate of tax on motor fuel (Parry and Small, 2005). In addition, many other developed countries raise a large share of revenue from gasoline tax (West and Williams, 2004). There have been a vast number of own-price elasticity studies for gasoline demand, which conclude that gas elasticity is relatively small, particularly in the short-run. Crucial challenges are hardly found for this conclusion. On the other hand, the cross-elasticity of gasoline demand with labor is much less known even though this is central to the Corlett-Hague rule. Corlett and Hague (1953-54) suggest a heavier tax on leisure complement commodities, thereby mitigating the distortion of income tax, which causes a loss of labor supply. The importance of cross-elasticity in an empirical work is emphasized by Goulder and Williams (2003). They find that it causes a significant bias to ignore the interaction between a new commodity tax and existing labor taxes. Therefore, the cross-elasticity of gasoline demand with leisure also should be considered carefully for an efficient taxation policy.

Only a few papers in recent literature study the cross-elasticities of gasoline with labor supply. One of the empirical works on gasoline cross-elasticity with leisure was performed by Madden (1995). Madden (1995) derives measurements for marginal revenue cost for indirect and direct taxation by including labor supply. Using Ireland's aggregate time-series data for the period between 1958 and 1988, the study measures two sets of marginal revenue costs for ten goods including gasoline based on estimates from a commodity demand and labor supply model. Weak separability for the relationship between ten goods and labor supply is assumed for a set of marginal revenue costs, and additive separability is assumed for the other set of marginal revenue costs. The comparison of the former and the latter does not show a significant sensitivity, and thereby, Madden (1995) concludes that the cross-elasticity with leisure has little impact on indirect tax reform.

The other study provided by West and Williams (2004) arrives at a quite different conclusion. They find that the cross-elasticity of gasoline has a significant effect, and it increases the optimal gas tax rate higher than the marginal damage. Unlike Madden's (1995), they use U.S. data from the CES, which is at the household level, from 1996 to 1998. This micro level data allows them to adopt a more flexible model, Almost Ideal Demand System, which is provided by Deaton and Muellbauer (1980). With this model, which does not constraint the cross-elasticity, they estimate all parameters including cross-elasticities, required for calculating the optimal gasoline tax policy. All compensated and uncompensated cross-elasticities estimated are positive, except compensated cross-elasticities of one adult household and female labor in two adults household. As a result, they conclude that the optimal tax is much higher than previous studies, assuming the separability. In addition, West and Williams (2004) propose higher elasticity of leisure driving demand than commuting driving demand, and less demand for commuting in the US as possible explanations.[13] Therefore, a further investigation with a conclusion of a more elastic demand for leisure-related driving than working-related driving would corroborate the findings that gasoline demand is relatively leisure complementary as a whole.

Going back to gasoline price-elasticity studies, it is not easy to investigate each price elasticity of *VMT* demand separately based on the purposes for driving (leisure/work).[14] The utility function for *VMT* by purpose requires more detailed variables such as travel time and costs, than needed to derive total *VMT*.[15] For this reason, Train (1986) estimates a discrete model for proportion of *VMT* independently from the total annual *VMT* model using the data on the length of each trip for one-day period. He just estimates probabilities of work-related proportion of *VMT* and leisure purpose *VMT* with several variables including gasoline price. The result indicates leisure purpose of *VMT* is more sensitive than work purpose, to gasoline price. On the other

[13] Parry and Small (2005) also allow weakly separable leisure in utility to compare the optimal gasoline tax for the UK and the US, and mention that a more complementary good to leisure tend to have more elastic demand.

[14] We just use the term leisure to indicate no work-related use. Work-related use usually include working and schooling, thus all other activities are included in non-work, which is shown as leisure here.

[15] We do not have such data available that distinguish the purposes for every single trip for a time period that is enough to estimate reliable elasticities, although day period of such data for each individual is available.

hand, using Canadian households' data, Berkowitz et al. (1990) jointly estimate both the continuous driving demand model and the discrete work- mode choice model, which has other alternatives such as transit and carpool.[16] They pay attention to the fact that most part of the work-related purpose of driving is commuting where distance is mostly fixed in the short-run. Estimated probability from work mode-choice model is employed to distinguish work-related gasoline demand and leisure-related gasoline demand in total operating cost or gasoline consumption. Then, both elasticities of work use and of leisure are jointly estimated. The results show that the price elasticity of leisure-related driving does not show much difference from work related driving.

In addition, the substitutability of driving consumption to other alternatives can be a good method to observe the elasticity of work-related driving demand. Bento et al. (2003) study the commute mode choices of US households. Adopting McFadden's (1974) model, they study the commuting choice among driving, walking or bicycling, bus, and rail. Because this model includes the gasoline cost of driving per mile, the different substitution behaviors to gasoline price can be observed in the commuting choice model. Therefore, the commuting choice model not only allows us to observe the substitutability of work purpose driving, but also to estimate the elasticities for purposes, work, and leisure.

[16] The survey was conducted for the purpose of their study.

3. The Model

Based on the household production theory, which is generally accepted for gasoline demand studies, the gasoline consumption by itself does not directly involve households' utility. Rather, the households' utility will be affected by Vehicle Miles Traveled (*VMT*), where *VMT* is the final consumption service provided by gasoline used by vehicles. Therefore, our study treats the *VMT* as a consumption commodity and the household vehicle as capital. In other words, the household utility function contains *VMT* as one of commodities, and this utility function will be conditional on the vehicle choice since *VMT* per gallon of gasoline varies depending on the vehicle choice. Using household conditional indirect utility function, this section describes both how households decide on their vehicles and how their conditional demand for *VMT* is determined. In addition, this section also shows how these decisions should be connected for consistent estimation. In the process, our study uses methods developed by Goldberg (1998) and West (2004). These models were originally built by Dubin and McFadden's (1984) and Goldberg (1998) and West (2004) modified them.

The first model in this section is the discrete vehicle choice model. In this model, the household is assumed to maximize its indirect utility through the vehicle choice. Each household makes one particular vehicle choice j, from the alternative vehicle choices, {*1, 2,…, J*} by comparing the underlying utilities. This can be expressed as

$$U_j = \max(U_1, U_2, \cdots, U_J) \tag{3.1}$$

This indicates that the actual choice made by the household is assumed higher than any other alternative. Its probability to choose is

$$P_j = \text{Prob}(U_j > U_k \text{ for all } j,\ j \neq k) \tag{3.2}$$

To estimate this probability, the set of alternative vehicle choices should be specified. Our study assumes that each alternative choice is composed of the number of vehicles owned n, the age of vehicle a, and the type of vehicle t. This portfolio is expressed as (n, a, t) to indicate each alternative choice j. The portfolio decision is then classified into two levels to ensure that the Independence from Irrelevant Alternatives (IIA) assumption holds, which indicates that the odds ratios of P_j / P_k are independent from any other alternatives. In particular, households decide how many vehicles they own n at the first step, which means that J alternatives are nested into N subgroups, $n = \{0, 1, \ldots, N\}$ on the first nest. Then, the households decide the combinations of vehicle ages and types (a, t) on the second nest conditional on the number of vehicles n chosen from the first nest. Thus, the joint probability of the alternative (n, a, t) to be chosen is decomposed as

$$P_j = P_{n,a,t} = P_n P_{a,t|n} \tag{3.3}$$

where $P_{n,a,t}$ is the joint probability that a household chooses (n, a, t), P_n is the marginal probability that n is chosen and $P_{a,t|n}$ is the probability that (a, t) is chosen conditional on n. This specification is based on the reason that the *VMT* demand of a household, which is the main concern in this study, varies more with the number of vehicles, their age and type rather than by other vehicle characteristics, where number of vehicles varies more than vintage and types.[17] Therefore, nesting these important characteristics in this

[17] More details on the classifications are shown in section 4.

way enables us to relax the IIA assumption. Finally, the probability is estimated by a nested logit model, developed by McFadden (1978), as follows,

$$P_n = \frac{e^{X_n\chi+\lambda_n I_n}}{\sum_{n=1}^{N} e^{X_n\chi+\lambda_n I_n}} \text{ and } P_{a,t|n} = \frac{e^{Z_{a,t|n}\gamma}}{\sum_{j=1}^{J} e^{Z_{a,t|n}\gamma}} \tag{3.4}$$

where inclusive value for the nth nest is $I_n = \ln\sum_{j=1}^{J_n} e^{Z_{a,t|n}\gamma}$, X_n and $Z_{a,t|n}$ are vectors of explanatory variables on the first and the second levels, and χ, γ and λ_n are parameters.[18]

The second part of the section presents the household continuous *VMT* demand model. Households are assumed to maximize their utility through *VMT* consumption, given their vehicle choice alternative j. The functional form of household conditional indirect utility is specified first, and then the household conditional *VMT* demand is derived from the utility function. As mentioned earlier, this study just follows theatrical approaches from previous studies. In particular, we borrow the specified form of the conditional utility as well as the way to derive the demand and to connect it with the discrete choice from West (2004). Specified conditional indirect utility is expressed as

$$U_j = (\alpha_0^j + \frac{\alpha_1}{\beta} + \alpha_1 p_j + H\delta + \beta(y - r_j) + \eta)e^{-\beta p_j} + \varepsilon_j \tag{3.5}$$

where p_j is the price per VMT_j; in other words, it is the operating cost per mile for the vehicle portfolio j. H is a vector of household characteristics, y is household annual total income, r_j is the annualized life cycle cost of the vehicle portfolio j and α_0^j is a

[18] The parameter λ_n indicates the correlation of errors for the alternatives in the same nest, N (McFadden, 1978).

constant for the j portfolio. α_1, β and δ are parameters and η and ε_j are unobserved characteristics for the households and vehicle portfolio j. In addition, the annualized life cycle cost of the j vehicle portfolio r_j is assumed to include two types of costs; one is the annual operating cost, $p_j q_j$, and the other is the rental cost, r_{rj}, as follows,

$$r_j = p_j q_j + r_{rj} \tag{3.6}$$

where q_j is the typical annual *VMT* by the household of vehicle portfolio *j* and r_{rj} is the rental cost of vehicle portfolio j.

Before deriving the demand equation from this utility function, recall the discrete vehicle choice model, which applies to this specific function. The function (3.5) can be rewritten as

$$U_j = V_j(p_j, H, y - r_j) + \eta e^{-\beta p_j} + \varepsilon_j \tag{3.7}$$

where $V_j(p_j, H, y - r_j)$ is an observed part and $\eta e^{-\beta p_j} + \varepsilon_j$ is an unobserved part of the utility. In order to employ the nested logit model that has been discussed earlier, the unobserved part, $\eta e^{-\beta p_j} + \varepsilon_j$, should be independently distributed according to type I extreme values.[19] Although the error term ε_j is assumed to be independently distributed according to type I extreme value distribution, the generalized extreme value assumption is not guaranteed for the entire unobserved part due to the first component of the error, $\eta e^{-\beta p_j}$ which, varies based on p_j. Therefore, Taylor series expansion around the mean

[19] According to McFadden (1974), the conditional logit model requires that the error term be distributed independently identically with the extreme value distribution.

price per VMT_j is applied to eliminate $\eta e^{-\beta p_j}$, following previous studies.[20] As a result, $\eta e^{-\beta \bar{p}}$ is not affected by vehicle choice. We have the function expressed as $U_j = V_j(p_j, H, y - r_j) + \varepsilon_j$. The probabilities discussed earlier can be estimated by the nested logit model under the generalized extreme value assumption on ε_j.

Reverting back to the continuous model, the conditional demand function can be derived from the specified conditional indirect function, (3.5), using Roy's identity. The demand for *VMT*, conditional on the vehicle portfolio choice j is

$$VMT_j = -\frac{\partial U_j / \partial p_j}{\partial U_j / \partial y} = q_j + \alpha_0^j + \alpha_1 p_j + H\delta + \beta(y - r_j) + \eta . \qquad (3.8)$$

For the estimation purposes, this conditional demand, given the vehicle portfolio j, can be expressed with indicators as follows,

$$VMT_j - q_j = \sum_{i \in J} \alpha_0^i \psi_{ji} + \alpha_1 \sum_{i \in J} p_i \psi_{ji} + H\delta + \beta(y - \sum_{i \in J} AOC_i \psi_{ji}) - \beta \sum_{i \in J} r_{ri} \psi_{ji} + \eta \qquad (3.9)$$

where ψ_{ji} is the indicator of vehicle portfolio, which is equal to 1 when $j = i$. AOC_i is the annual operating cost of vehicle portfolio, which represents $p_i q_i$. This equation would be the final form of the consistent estimation for the *VMT* demand if the possibility of correlation between the indicator ψ_{ji} and the error term η was excluded. Unfortunately, it is not reasonable to expect that households do not have any unobserved factor that affects both *VMT* demand and vehicle choice decisions. Therefore, this study allows the possibility of correlation. The error term η can be decomposed into two parts as follows,

[20] This approach is first suggested by Mannering and Winston (1985). Goldberg (1998) and West (2004) follow their approach.

$$\eta = E(\eta \mid j) + \xi \tag{3.10}$$

where $E(\eta \mid j)$ is the conditional expectation of η, given the vehicle portfolio j. ξ is an error term that is independent from vehicle choice. Dubin and McFadden (1984) provide the solution for $E(\eta \mid j)$ if the probabilities are assumed a conditional logit:

$$E(\eta \mid j) = \sum_{i \neq j}^{J} \left[\frac{\rho_i \sqrt{6\sigma^2}}{\pi} \right] \left[\frac{P_i \ln P_i}{1 - P_i} - \ln P_j \right] \tag{3.11}$$

where ρ_i is a correlation of η with ε_i, and σ^2 is an unconditional variance of η. In order to apply the correction term into our model, we fortunately do not need to know $\frac{\rho_i \sqrt{6\sigma^2}}{\pi}$. In a logit model, since probabilities are estimated based on utility differences and not absolute values, any unobserved factor that increases the relative utility from one of the vehicle choices must decrease the relative utility from other alternatives by the same amount. Therefore, ρ_i is necessarily equal to $-\rho_j$ (Train, 1986). Finally, the equation including this correction term for the estimation can be expressed as follows,

$$VMT_j - q_j = \sum_{i \in J} \alpha_0^i \psi_{ji} + \alpha_1 \sum_{i \in J} p_i \psi_{ji} + H\delta + \beta(y - \sum_{i \in J} AOC_i \psi_{ji}) - \beta \sum_{i \in J} r_{ri} \psi_{ji}$$

$$+ \theta \sum_{i \neq j}^{J} \left[\frac{\hat{P}_i \ln \hat{P}_i}{1 - \hat{P}_i} + \ln \hat{P}_j \right] + \xi \tag{3.12}$$

where θ is the parameter containing $\frac{\rho_i \sqrt{6\sigma^2}}{\pi}$ and $\hat{P}_i$ and $\hat{P}_j$ are the estimated probabilities from the discrete vehicle choice model. This estimation equation gives us consistent results by allowing and correcting the possibility of the correlation between the discrete vehicle choice and the continuous *VMT* demand.

In addition, our study analyzes heterogeneous behaviors of household depending on their income levels within each public transit supply areas. Therefore, the equation (3.12) includes an interaction term between the price of *VMT* and net income.[21]

[21] Including the interaction term may give rise to a discord between the final estimation and the specified utility function this section has discussed (West, 2004).

4. Data and Summary Statistics

4.1 Data Description

In order to analyze the effects of gasoline tax through various responses of households, our study employs reliable datasets on households, vehicles, and residential areas. Eight sources of data from different agencies are collected and merged.

4.1.1 Household Characteristics

The primary data for our empirical analysis is drawn from the 2001 National Household Travel Survey (NHTS) conducted by the U.S. Department of Transportation from March 2001 through May 2002.[22] This survey is an updated series of both the Nationwide Personal Transportation (NPTS) and American Travel Survey (ATS), which have broadly been used for studies on the travel behaviors of Americans.[23] Although the 2001 NHTS is a cross-sectional survey, which does not contain any household behavior change of a household over time, it does provides the most recent and detailed micro data on the travel behavior and characteristics of American households.

The data is collected through household and personal interviews, and odometer readings.[24] Participants are selected by a random-digit dialing procedure from the

[22] The retail gasoline price in this period of the survey was relatively stable. The average price of retail gasoline price during the survey was about $1.32 and the standard deviation was 0.18. See figure A1 in the appendix.

[23] NPTS was conducted in 1967, 1977, 1983, 1990, and 1995, and ATS was conducted in 1977 and 1995.

[24] Odometer readings are collected at two points during the survey with at least two-month interval between the first and the second interviews. The NHTS provides two types of vehicle miles traveled (*VMT*), annual miles reported by interviewees, and the estimated annual miles based on odometers between two interviews,

nationwide non-institutionalized population of the US. Interview questions include details of household and personal characteristics, vehicle attributes, and daily and long-distance trips. In particular, the dataset includes the crucial information needed to estimate the parameters in both the vehicle choice model and *VMT* decision model discussed earlier. It includes the annual vehicle miles driven, household annual income, fuel efficiency of vehicle, state of employment, and other demographic and geographic household characteristics.[25]

Since our model is based on a household maximization, the main dataset is constructed on a household unit basis. Our study uses 22,290 household observations after eliminating the observations that were missing information on the crucial variables and outliers from the total 69,817 households in the published dataset.[26] In addtion, sampling weights provided by the NHTS at the household level are used for our estimates to adjust sampling errors.

Other than the data collected from household interviews, the NHTS has added more information from different data sources on vehicle attributes and the location for

---

household and personal characteristics, vehicle attributes, location, weather, etc. Our study employs the annual miles that interviewees report if available, otherwise, use the estimated annual miles instead. 43,163 vehicles have self-reported *VMT* out of 53,278 vehicles.

[25] Annual income is reported in ranges, not in actual amounts. Therefore, midpoints of each income interval are taken and assigned to each household. For the highest income range, the average annual income of households from the *Panel Study of Income Dynamics (PSID)* is used. Households whose income is higher than $90,000 and who own less than two vehicles are taken from 2001 *PSID*.
"The Panel Study of Income Dynamics is primarily sponsored by the National Science Foundation, the National Institute of Aging, and the National Institute of Child Health and Human Development and is conducted by the University of Michigan."

[26] The observations that miss the crucial data are deleted, on annual *VMT*, annual income, gasoline price, the total public transit service miles in the residential areas and the number of adults in the household. In addition, households owning more than two vehicles are deleted (more details are shown in the following section 4.2). The vehicles whose annual miles are less than 300 miles or more than 60,000 miles are assumed outliers. See footnote 35 for more details.

each household such as fuel efficiency and average gasoline price for each state. However, some of this data is inappropriate for our analysis. Therefore, seven more sources of data from different agencies are collected and merged with the NHTS. Three sources of data contain the information on vehicle attributes, and four sources of data contain information on the household residential areas. The NHTS fortunately provides identifications of each vehicle and location for each household. It includes the name of makes, models, and years for each vehicle households own, and it has a name of MSA, CMSA, and state for the location of every household.[27]

4.1.2 Vehicle Attributes

Additional detailed data on vehicle attributes is taken from three different sources – Ward's Automotive Yearbook from 1976 to 2002, the National Automobile Dealers Association's (NADA) 2001 April Official Used Car Guide, and the National Transportation Statistics (NTS) 2002 published by Bureau of Transportation Statistics (BTS).

Ward's Automotive Yearbook has been published every year since 1938 by Ward's communications. This yearbook includes detailed vehicle information for most vehicles in the US vehicle market. It has information on price, horsepower, fuel efficiency, and length for each vehicle. Our study use this information to estimate the used car price and the depreciation rate, accompanied with the used car price data drawn

[27] Consolidated Metropolitan Statistical Area (CMSA) is the geographic classification defined by the U.S. Census Bureau. It has one or more MSA, which have strong social and economic links including commuting patterns. Metropolitan Statistical Area (MSA) is the geographic classification defined by the U.S. Census Bureau. It has one or more cities where the population is more than 50,000.

from the 2001 April NADA Official Used Car Guide.[28] The estimations of the used car price and the depreciation rate are necessary to compute the rental cost of each vehicle portfolio. In addition, fuel efficiency information is drawn from Ward's for the vehicles that the NHTS does not provide.[29] These data are merged with the NHTS by matching up the identified variables – vehicle makers, year and model names.[30] In addition, data for average maintenance and tire cost based on vehicle year are provided by U.S. Department of Transportation, Bureau of Transportation Statistics (2002) to compute the *VMT* price with gasoline price and fuel efficiency.[31]

4.1.3 Residential Areas

The data on household residential areas is collected from four different sources – ACCRA Cost of Living Index, 2000 U.S. Census, National Transit Database (NTD) and Highway Taxes and Fees, provided by the Federal Highway Administration (FHWA).

Although the NHTS provides the data on pre-tax state-level gasoline prices, our study instead uses the gasoline prices taken from the Cost of Living Index, published

[28] NADA Official Used Car Guide is published by National Automobile Dealers Association. It includes eight years of used car prices for each specification of vehicles. Total number of the used car prices for the models from the NADA is 1,271 while the Ward's has 5,090 vehicle model entries.

[29] The 2001 NHTS includes fuel efficiency information, provided by the U.S. Environmental Protection Agency (EPA). These data are used if available; otherwise, the data on fuel efficiency from Ward's are used for the vehicles that the NHTS misses.

[30] The data from the Ward's is aggregated to merge with the NHTS because the most detailed vehicle information the NHTS has is the vehicle model. The classification of models by the NHTS ignores additional specifications each model could have such as the engine size (which are optional for some vehicles), trims (such as sedan and coupe), and other options. Vehicles could have different specifications of price, size, and performance depending on these differences. The specifications within each model are averaged for the data from the Ward's. In a similar way, used car prices from NADA are aggregated, after taking the basic option prices, to merge with others.

[31] This is provided on "http://www.bts.gov/publications/national_transportation_statistics/2002/"

quarterly by American Chamber of Commerce Researchers Association (ACCRA). It provides prices for consumer goods and services, which include the after-tax average price of regular unleaded gasoline for 302 U.S. urban areas. our study uses the average gasoline prices from the second quarter of 2001 to the first quarter of 2002, instead of state-level gasoline prices in 2001 NHTS. There are two reasons for this. First, since gasoline prices are one of the most crucial variables in our models – the variations in gasoline prices that households face, depending on location, should be reflected in the model or else the model would underestimate the price elasticities. Secondly, our study takes the different accessibility of transit systems into consideration, depending on households' residential areas, and ignores the variations in gasoline prices among the residential areas, which can overestimate the effects of public transit. Therefore, we take an average of the gasoline prices from the index within MSA and CMSA levels, which are the lowest geographic units for the NHTS households.

Other important information on household residential areas is taken from 2001 NTD. This dataset, reported by the Federal Transit Administration (FTA), includes financial and operating information for 534 public transit agencies.[32] Our study uses this data on actual public transit vehicle miles and rail miles to measure the public transit supply in residential areas. The ferryboat agencies are excluded. As a result, 528 agencies remain in our sample. Then, to assign total annual transit miles to each household's residential area, annual service miles from all agencies are summed up within each MSA and CMSA level. Since 24 agencies serve more than one MSA or CMSA areas, for these agencies, we take an un-weighted average of the service miles

[32] See "http://www.ntdprogram.com/ntdprogram/pubs/dt/2001/DataTable01.htm" for more details.

according to the numbers of service areas, and allocate them to each MSA or CMSA. Along with the service miles, the data on the size of each area in square miles provided by the 2000 U.S. census is also used to measure the public transit supply in residential areas.

The last additional residential information is vehicle registration fees for each state. These data are provided by the Office of Highway Policy Information of the US FHWA.[33] The vehicle registration fee according to the state of residence is assigned to each household.

4.2 Vehicle Choice Portfolios and Main Variables

Using the data described in the section 4.1, this section describes the vehicle choice portfolios and the main variables. In particular, the specified classifications of vehicle choice portfolios and the specified calculations for the main variables are shown to apply the model in section 3 to our sample.

4.2.1 Vehicle Portfolios

The vehicle choice portfolios are classified into 16 nested groups, depending on the number of vehicles per household, vehicle types, and vintage.[34] This simplification of vehicle choice enables the model to sidestep the limitations of the data and the

[33] The website, http://www.fhwa.dot.gov/ohim/hwytaxes/2001, provides the Summary of State Motor-Vehicle Registration Fee Schedules for 2001.

[34] The most similar classification is shown in Feng et al. (2005). They classify the vehicle choice by the number of vehicles (0, 1, 2) and the type of vehicle (a Car and an SUV). In addition, they treat the vintage as a continuous variable.

complications of the regressions while capturing the most important determinants of vehicle attributes that affect the *VMT* demand decision.

Our sample shows that *VMT* varies mostly by the number of vehicles per household. Therefore, the first nest is classified by the number of vehicles, (0, 1, 2).[35] Then, within each number of vehicle choice, the second nest is classified by the combinations of the vehicle type and vintage, which are expected to affect *VMT* decision more than other vehicle attributes. Mostly, as Feng et al. (2005) mention, because of the different applications of Corporate Average Fuel Economy (CAFE) standards for cars and SUVs, two different vehicle types show a significant difference in fuel efficiencies.[36] Therefore, the vehicles are classified into two types, (Sedans, SUVs). Second, along with the vehicle type, the vehicles are classified into three different vintage choices, (New, Medium, Old): New includes the vehicles newer than 1996; Medium vehicles are those between 1989 and 1996; and Old vehicles are older than 1989. For two vehicle households, we set vintage to that of the newer vehicle. For example, owing a 1999 Sedan and a 1985 SUV belongs to the portfolio, (New, Sedan and SUV). As a result, we

---

[35] Our study only includes passenger cars and light trucks (other trucks, RVs, motorcycles and others are excluded). Also, the vehicles are excluded, whose annual miles are less than 300 miles or more than 60,000 miles since these vehicles could be owned for unusual purposes such as a collection or a business (Bento et al. (2005) exclude the vehicles below 100 miles or above 60,000 miles). Eliminating these vehicles, eighty percent of households in the sample own two or less vehicles. Following most previous studies, I exclude the households that have more than two vehicles due to the regression complications and the data limitation. As a result, as West (2004) mentions, the exclusion would cause the study to include more households in relatively lower income portions of the distribution because households whose incomes are higher tend to own more vehicles.

[36] The fuel economy (MPG) regulation enacted in 1975. In our study, car means a passenger car and the SUV means a light truck including van, pickup truck and SUV. Figure A2 in the appendix shows the differences of average MPG for each vehicle type in our sample.

have six combinations for single vehicle households, and nine combinations for two-vehicle households.[37]

4.2.2 Main Variables

The continuous *VMT* demand decision model discussed in section 3 is conditional on the particular vehicle portfolio choice. Therefore, some of variables in the model are first given by the choice of the vehicle and then vary across households depending on their characteristics. Following previous studies, these variables are calculated to represent both household and vehicle choice characteristics. We borrow the specifications of the rental cost, *VMT* price, and the typical annual *VMT* from Bento et al. (2005) and West (2004).[38] First, the calculation for the rental cost of j vehicle portfolio, r_{rj} is expressed as follows,

$$r_{rj} = (1+R)(D_j + F) \tag{4.1}$$

where R is the real interest rate, 3.89 percent, which is also the average real 30-year T-bill yield in 2001, D_j is the real depreciation for the vehicle portfolio j, and F is the registration fee in the state level of household's residential area. For real depreciation, estimated used car prices in 2001 and the depreciation rate are used.[39] The fitted equation is as follows.

---

[37] This portfolio structure and significant differences in the main variables by the vehicle portfolios are shown in table A1 in the appendix.

[38] Bento et al. (2005) have additional data on insurance cost and repair costs.

[39] Since NADA does not contain the used car prices for every car in our sample, the estimated used car prices are used when the prices are missed. Otherwise, the prices from NADA are used.

Table 1: Fitted Model for Used Car Price and Depreciation Rate
Dependent Variable: ln (Used Car Price); (Standard Errors in parentheses)

Cons.	ln(price)	Vintage	ln(HP)	ln(length)	ln(MPG)	Luxury	Europe	Japan	Van	SUV	Pickup
2.872	0.790	-0.160	0.302	-0.359	-0.320	0.134	0.278	0.177	0.002	-0.036	-0.054
(0.64)	(0.04)	(0.003)	(0.04)	(0.10)	(0.06)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)

The adjusted R^2 is 0.92; Number of observations are 5,090.
Note: HP is horsepower; Luxury is equal to one if the vehicle make is Lincoln, Cadillac, Audi, BMW, Mercedes-Benz, Porsche, Acura, Infiniti, Lexus, or Land Rover. Europe and Japan are equal one if the vehicle make is originated in each area. Van, SUV, and Pickup are equal to one if the vehicle type belongs to those. Definitions of vehicle types used here are different from the main classification for the portfolios in our vehicle choice model. SUV includes Van, SUV, and pickup in the vehicle choice study.

The estimated used car prices are multiplied by the depreciation rate and then the average real depreciations are assigned to each portfolio. Second, the *VMT* price is specified as follows,

$$p_j = \frac{p^{gas}}{MPG_j} + M_j + T_j \tag{4.2}$$

where P^{gas} is the average gasoline price within the MSA or CMSA level, MPG_j is the unadjusted 55/45 combined fuel economy, M_j and T_j are the average costs of maintenance and tire per mile in portfolio j.[40] Third, the typical annual *VMT* is calculated based on a regression of average *VMT* in each portfolio on the household characteristics. The fitted equation is as follows.

[40] By EPA, the unadjusted combined fuel economy is defined as,

$$MPG = \frac{1}{0.55 * \frac{1}{MPG_{EPAcity}} + 0.45 * \frac{1}{MPG_{EPAhighway}}}$$

where $MPG_{EPAcity}$ and $MPG_{EPAhighway}$ are city driving only fuel economy and highway driving only fuel economy.

Table 2: Fitted Model for Typical Miles
Dependent Variable: Average *VMT* in each portfolio (Robust Standard Errors in Parentheses)

Intercept	Total Annual Income	Number of Drivers per household
1287.21	0.0421	7498.54
(189.02)	(0.0020)	(158.74)

R^2: 0.5319, Number of Observations: 22,290

Vehicle choice attributes are reflected by averaging the *VMT* in each portfolio. Household characteristics are then reflected by the regression. Household characteristics include total annual income and the number of drivers in the household.

Another important variable to be calculated is the public transit supply. Following Bento et al. (2003), total annual transit service miles are used as a proxy variable, to measure the supply of public transit in the residential area. The public transit supply is calculated as follows,

$$Transit\ Supply = \frac{Annual\ Total\ Routine\ Miles}{Total\ Squres\ Miles} \tag{4.3}$$

where $Annual\ Total\ Routine\ Miles$ is a sum of annual service miles provided by each transit agency in residential areas (MSA or CMSA), $Total\ Squres\ Miles$ is the size in square miles for areas (MSA or CMSA).

This proxy for public transit supply is used in both vehicle choice and *VMT* demand model in two ways. First, it is used as a continuous proxy variable in the first nest in the vehicle choice model, which is also the household choice of vehicle quantity. Second, indicator variables are created based on this proxy, and are used in the second nest in the vehicle choice model, and also used to split the total sample in the *VMT* demand model to analyze the different responses of households depending on public transit supply.

In order to create transit-supply indicator variables, households in the total sample are separated into two groups. One group includes households who belong to CMSA and MSA areas identified by 2001 NHTS, and the other group includes households living in MSA areas of less population than 1 million. The latter group is not identified by names of MSA, but instead, is aggregated by state level in 2001 NHTS. The households in identified CMSA and MSA areas are split into four levels with approximately same proportion of observations based on their public transit supply. State aggregated households in MSA areas of less than 1 million in size are treated as one indicator variable. As a result, five levels of transit supply indicators are created. More details about public transit supply indicators of CMSA and MSA are shown in table A2 in the appendix.

4.3 Summary Statistics

In order to summarize household data in our sample, four tables are presented. The first three tables are provided in order to examine the relation between the key variables, including household characteristics, and vehicle choices, composed with three vehicle attributes. The last table is provided to see different levels of *VMT* demand depending on household characteristics.

Table 3 tabulates averages and proportions of the key variables with the number of vehicles. The averages in the table show that households own more vehicles as they have more members, more workers, more drivers, and more annual income. The proportions of household characteristics indicate that the tendency to own more vehicles increases if a household is white, homeowner and faces less transit supply while the tendency decreases if he lives in an urban area, or lives in MSA with rail or more transit supply. In addition, vehicle miles, rental cost, and *VMT* price increase as households own more vehicles.

Table 3: Household Characteristics and Vehicle Attributes by Number of Vehicles

Household Characteristics and Vehicle Attributes	Number of Vehicles Households Own			
	0	1	2	Total
Number of Households	2,751	9,180	10,359	22,290
Number of Household Members	1.862	1.878	2.954	2.348
Number of Household Members with Jobs	0.678	0.880	1.540	1.143
Number of Drivers per Household	0.497	1.273	2.013	1.497
Total Household Income last 12 months ($)	23,244	40,531	72,214	52,180
Worker Ratio per household	0.447	0.645	0.759	0.669
(%) Respondents are white	44.95	71.47	80.09	71.82
(%) Households in urban area	93.68	87.76	82.10	86.04
(%) Households in MSA with Rail (subway)	54.52	37.68	31.79	37.28
(%) Homeowners	22.50	49.34	75.00	57.12
(%) Households in MSA [a] with transit supply: > 28,000	27.71	9.69	6.21	10.49
(%) Households in MSA with transit supply: 28,000 - 13,000	22.97	22.47	20.99	21.88
(%) Households in MSA with transit supply: 13,000 - 6,450	16.11	20.72	21.83	20.61
(%) Households in MSA with transit supply: < 6,450	14.20	19.15	21.87	19.71
(%) Households in MSA of less than 1 million [b] : 1,464	19.01	27.98	29.10	27.31
(%) Households with annual income < 17,500: Quintile 1	65.90	26.55	6.63	22.91
(%) Households with annual income 17,500 – 32,500: Quintile 2	16.60	28.00	13.06	19.98
(%) Households with annual income 32,500 – 47,500: Quintile 3	8.83	20.92	20.98	19.38
(%) Households with annual income 47,500 – 72,500: Quintile 4	3.61	14.17	24.46	17.31
(%) Households with annual income > 72,500: Quintile 5	5.06	10.36	34.88	20.42
Vehicle Miles Traveled (mile)	0	10,753	23,894	15,122
Rental cost ($)	0	883	2,127	1,314
VMT price ($)	0	0.097	0.101	0.086

[a] MSAs indicate both CMSAs and MSAs of more than 1 million populations. 2001 NHTS classifies MSAs into two, an MSA of more than 1 million populations and an MSA of less than 1 million. Since MSAs of less than 1 million are not identified, they are aggregated by state level. More details are shown in the table A2 in the appendix.

[b] Average transit supply is 1,464

Table 4: Household Characteristics and Vehicle Attributes by Vehicle Types

Household Characteristics and Vehicle Attributes	Number of Vehicles Households Own					
	Sedan	SUV	Sedan Sedan	Sedan SUV	SUV SUV	Total
Number of Households	6,986	2,194	3,074	5,474	1,811	19,539
Number of Household Members	1.813	2.094	2.630	3.041	3.300	2.420
Number of Household Members with Jobs	0.839	1.015	1.530	1.530	1.588	1.212
Number of Drivers per Household	1.264	1.302	2.019	2.009	2.012	1.645
Total Household Income last 12 months ($)	39,264	44,712	70,604	72,382	74,742	56,471
Worker Ratio per household	0.615	0.744	0.742	0.760	0.790	0.702
(%) Respondents are white	70.24	75.56	74.14	82.33	84.44	75.81
(%) Households in urban area	89.25	82.82	90.33	79.59	74.26	84.91
(%) Households in MSA with Rail (subway)	38.6	34.66	39.42	28.79	26.58	34.72
(%) Homeowners	48.54	51.99	69.5	75.93	82.5	62.25
(%) Households in MSA [a] with transit supply: > 28,000	10.09	8.35	8.42	5.1	5.46	7.94
(%) Households in MSA with transit supply: 28,000 - 13,000	24.04	17.29	25.17	19.31	18.22	21.72
(%) Households in MSA with transit supply: 13,000 - 6,450	19.8	23.72	22.55	21.64	21.08	21.28
(%) Households in MSA with transit supply: < 6,450	19.45	18.17	20.51	22.5	22.53	20.52
(%) Households in MSA of less than 1 million [b]: 1,464	26.61	32.48	23.35	31.46	32.7	28.54
(%) Households with annual income < 17,500: Quintile 1	28.43	20.33	7.66	6.5	5.09	16.53
(%) Households with annual income 17,500 – 32,500: Quintile 2	28.84	25.2	13.64	12.78	12.81	20.48
(%) Households with annual income 32,500 – 47,500: Quintile 3	19.52	25.54	22.06	21.06	18.68	20.95
(%) Households with annual income 47,500 – 72,500: Quintile 4	13.34	16.9	22.59	24.79	26.96	19.34
(%) Households with annual income > 72,500: Quintile 5	9.86	12.03	34.04	34.88	36.46	22.7
Vehicle Miles Traveled (mile)	10,002	13,229	22,260	24,045	26,518	17,364
Rental cost ($)	819	1,092	1,838	2,215	2,402	1,509
VMT price ($)	0.092	0.112	0.093	0.103	0.113	0.099

[a] MSAs indicate both CMSAs and MSAs of more than 1 million populations. 2001 NHTS classifies MSAs into two, an MSA of more than 1 million populations and an MSA of less than 1 million. Since MSAs of less than 1 million are not identified, they are aggregated by state level. More details are shown in the table A2 in the appendix.

[b] Average transit supply is 1,464

Table 4 tabulates averages and proportions of the key variables with the vehicle types. On average, households have a greater tendency to own SUVs as they have more members, more workers, and higher annual income. It is ambiguous if the number of drivers in two vehicle households affects the choice of portfolio to include more SUVs, while it seems a one-vehicle household having more drivers has a greater tendency to own an SUV instead of a Sedan.

Table 5: Household Characteristics and Vehicle Attributes by Vehicle Vintages

Household Characteristics and Vehicle Attributes	Vintage of Vehicles Households Own			
	New	Medium	Old	Total
Number of Households	12,867	5,518	1,154	19,539
Number of Household Members	2.515	2.287	2.163	2.420
Number of Household Members with Jobs	1.314	1.084	0.882	1.212
Number of Drivers per Household	1.742	1.531	1.307	1.645
Total Household Income last 12 months ($)	66,887	41,615	30,202	56,471
Worker Ratio per household	0.734	0.669	0.576	0.702
(%) Respondents are white	78.58	72.42	66.6	75.81
(%) Households in urban area	84.62	84.94	87.14	84.91
(%) Households in MSA with Rail (subway)	34.64	35.06	34.04	34.72
(%) Homeowners	69.17	53.4	40.73	62.25
(%) Households in MSA [a] with transit supply: > 28,000	8.11	7.32	9.02	7.94
(%) Households in MSA with transit supply: 28,000 - 13,000	21.84	21.81	20.4	21.72
(%) Households in MSA with transit supply: 13,000 - 6,450	21.42	21.32	19.93	21.28
(%) Households in MSA with transit supply: < 6,450	20.89	20.65	16.98	20.52
(%) Households in MSA of less than 1 million [b]: 1,464	27.73	28.91	33.67	28.54
(%) Households with annual income < 17,500: Quintile 1	8.55	26.09	43.86	16.53
(%) Households with annual income 17,500 – 32,500: Quintile 2	17.04	26.08	26.39	20.48
(%) Households with annual income 32,500 – 47,500: Quintile 3	21.09	22.15	15.03	20.95
(%) Households with annual income 47,500 – 72,500: Quintile 4	23.09	14.29	8.78	19.34
(%) Households with annual income > 72,500: Quintile 5	30.23	11.39	5.94	22.7
Vehicle Miles Traveled (mile)	20,165	13,730	8,877	17,364
Rental cost ($)	2,116	588	189	1,509
VMT price ($)	0.106	0.091	0.079	0.099

[a] MSAs indicate both CMSAs and MSAs of more than 1 million populations. 2001 NHTS classifies MSAs into two, an MSA of more than 1 million populations and an MSA of less than 1 million. Since MSAs of less than 1 million are not identified, they are aggregated by state level. More details are shown in the table A2 in the appendix.

[b] Average transit supply is 1,464

The proportions of household characteristics show that the households have a greater tendency to own SUVs if they are white and homeowners. In addition, it is worth noting that the characteristics of the residential area affect the choice of vehicles as well as the number of vehicles. Households in urban areas with rail have a lesser tendency to have SUVs. Similarly, households in MSA with more transit supply also have a lesser tendency to have SUVs. Vehicle miles, rental cost, and *VMT* price increase as households include SUVs in their vehicle choice portfolios.

Table 5 tabulates averages and proportions of the key variables with the vehicle vintages. On average, households tend to own newer vehicles as they have more members, more workers, more drivers, and more annual income. The percentages of households indicate that households tend to own newer vehicles if they are white and if they are homeowners. Unlike the quantity and the type of vehicles, it is ambiguous if household residential area affects the choice of vintage. Although it seems households living in urban areas own older vehicles, the rest of transit supply indicators including the presence of rail system, do not show a clear tendency. In addition, vehicle miles, rental cost, and *VMT* price increase as households own newer vehicles.

Finally, table 6 reports average *VMT* demand depending on households' characteristics. The demand for *VMT* increases if a household is white, a homeowner, and has more workers; it also increases, as the household annual income is higher. As expected, all public transit indicators show that the transit supply reduces the *VMT* demand. As the transit supply in the area increases, households tend to drive less. In addition, within the life cycle of household, the period of highest *VMT* demand comes from two adults or more, with the youngest child whose age is between 0 and 5.

Table 6: Average Demand for VMT by Household Characteristics

Household Characteristics		*VMT* Demand (Mean: 15,122)
If a respondent is white	NO	12,098
	YES	16,308
If a household is a home-owner	NO	12,027
	YES	17,446
If more than a half of adults in household work	NO	11,655
	YES	17,616
Household annual income	Quintile 1	6,350
	Quintile 2	12,261
	Quintile 3	16,166
	Quintile 4	19,732
	Quintile 5	22,861
If a household in MSA with rail (subway)	NO	16,030
	YES	13,594
If a household lives in urban area	NO	19,440
	YES	14,421
MSA transit supply [a]	> 28,000	9,800
	28,000 ~ 13,000	14,451
	13,000 ~ 6,450	16,312
	< 6,450	16,563
If a household lives in MSA of less than 1 million [b]	NO	14,880
	YES	15,765
Household life cycle	1 adult, no children	10,658
	2+ adults, no children	19,967
	1 adult, youngest child 0-5	7,714
	2+ adults, youngest child 0-5	21,936
	1 adult, youngest child 6-15	10,777
	2+ adults, youngest child 6-15	21,899
	1 adult, youngest child 16-21	14,721
	2+ adult, youngest childe 16-21	17,710
	1 adult, retired, no children	4,577
	2+ adults, retired, no children	13,111

[a] MSAs indicate both CMSAs and MSAs of more than 1 million populations. NHTS classifies MSAs into two, an MSA of more than 1 million populations and an MSA of less than 1 million. Since MSAs of less than 1 million are not identified, they are aggregated by state level. More details are shown in the table A2 in the appendix.

[b] Average transit supply is 1,464

5. Empirical Results

Using the data described in section 4, vehicle choice and *VMT* demand models are sequentially estimated. First, the vehicle choice model is estimated adopting nested logit model structure. Then, the *VMT* demand model is estimated adopting the Dubin-McFadden correction method. The estimated probabilities from the first step are used to correct the bias in the demand model.

5.1 Vehicle Portfolio Choice Model

Parameters shown in (3.4) are estimated using the full maximum-likelihood method. The appropriateness of this nested structure for our sample is supported by a likelihood ratio test. From the LR test for the nested logit structure against null hypothesis of a non-nested conditional logit model, the χ^2 value of 2,558 suggests the use of the nested structure with our sample in a 1% significance level. The results of the two stage nested logit model is summarized as follows.[41]

The first level decision estimation includes number of workers, an indicator for home-ownership, total annual income, transit supply in the MSA, and the population density in those areas as explanatory variables which are expected to affect households' vehicle quantity choice decision. In addition, it contains inclusive-value variables, which indicate expected utility from the vintage and type decision given the vehicle quantity choice.

[41] The full result is shown in the table A4 in the appendix.

Table 7: Summary Results for Household Vehicle Choice Model

First Nest
< Number of Vehicles >

Variable	Coef.	Std. Err.	P > | z |
One Car * No. of Workers	0.30282	0.03784	0.000
One Car * Homeowner	1.73226	0.04965	0.000
One Car * Income	0.00003	0.00000	0.000
One Car * Transit Supply	-0.00013	0.00001	0.000
One Car * Pop. Density	0.00197	0.00014	0.000
Two Car * No. of Workers	0.47718	0.05231	0.000
Two Car * Homeowner	2.38282	0.06766	0.000
Two Car * Income	-0.00002	0.00000	0.000
Two Car * Transit Supply	-0.00020	0.00001	0.000
Two Car * Pop. Density	0.00020	0.00020	0.332
(Inclusive Value Parameters)			
* One Car	0.37975	0.01633	0.000
* Two Car	2.88793	0.15839	0.000

Second Nest
< Vintage and Type >

Variable	Coef.	Std. Err.	P > | z |
Rental Cost	0.00326	0.00007	0.000
Annual Operating Cost	0.00438	0.00013	0.000
VMT price	-117.96620	2.39558	0.000

Summary Features

Relationship (+,–) between Variables, and Vintage or Type

1. Income & New: +
2. Drivers per Household & New: –
3. Number of Households & Old: +
4. White [a] & Medium: +
5. Highest Income Quintile & New SUV: +
6. Number of Household & SUV: +
7. Urban & Sedan: +
8. Life Cycle 2 [b] & New: + ; Life Cycle 3 [c] & SUV: +

Note: number of observations is 399,264; number of households used is 24,954

log likelihood = - 46092.069; χ^2 = 46190.22

log likelihood ratio test of homoskedasticity (iv = 1): χ^2 = 2558.38 support the nested logit model.

[a] White is equal to one if a respondent of the survey is white.

[b] Household Life Cycle: youngest child's age is between 0 and 5.

[c] Household Life Cycle: youngest child's age is between 6 and 15.

The conclusions that can be drawn from this estimation are: first, more workers per household increase the probability to own two vehicles over one vehicle, and one over none; second, home-ownership increases the probability to own two vehicles over one vehicle, and one over none; third, it is likely that higher annual household income has little effect on the probability to choose none or two vehicles while it increases the probability of choosing one vehicle; fourth, transit supply in the area decreases the probability to own two vehicles over one, and one over none; finally, the population density increases the probability to own one vehicle over two, and two over none. It is worth noting that the population density does not decrease the probability of owning vehicles while transit supply does decrease it.

The second stage of the nested structure deals with a choice of the combinations of vintage and vehicle type, given the vehicle quantity choice. The equation includes three vehicle attributes. They are rental cost, annual operating cost, and *VMT* price. As expected, higher *VMT* price lowers the probability to own a vehicle. Besides using vehicle attributes, important household characteristics, which are expected to affect the vintage and type decision, are also used by interacting with vehicle choice portfolios, which implicitly contain vehicle attributes. Several important findings are summarized as follows. [42]

First, annual income of households affects households' vehicle choices. Higher income of households strongly increases the probability to own newer vehicles except portfolio 4 (New and SUV). [43] This explains why the result for vehicle quantity nest does not show a strong effect of annual income. Strong preferences of higher income households for owning only two New vehicles (portfolio 7, 10, and 13) are observed. The highest level of income households among five income quintiles also display strong tendency to own only New SUVs, but any other vintage SUVs. Second, environment of households residential areas affect the households vehicle choice. Households living in urban areas are likely to have more Sedan type vehicles. Higher transit supply also is likely to increase the probability for households owning the Sedan and Sedan combination slightly more than other combinations (Sedan and SUV, SUV and SUV), and lowers the likelihood to own an SUV for one vehicle households more than the Sedan type. Third, among household's life cycles, households with the youngest child

---

[42] See table A4 in the appendix for more details, in which the full result is shown.

[43] The interaction with the second highest income quintile households displays the highest coefficient increasing the probability choosing single New SUV.

between 0 and 5 are more likely to have New vehicles, and with the youngest child between 6 and 16 are more likely to have SUVs. From the coefficients on other indicators, we observe that having more household members increases the probability of including SUVs and Old vehicles as well. Number of drivers per household also has a negative relationship with New vehicles. In addition, white households display a preference for Medium vintage vehicles over others.

The main purpose of vehicle choice model in our study is to correct the bias in *VMT* demand model, which is used to simulate the income distributional effect under an additional gasoline tax. Nevertheless, some of results in vehicle choice model provide useful information on households' behaviors to analyze the gasoline tax policy. In particular, it is worth noting that public transit supply significantly reduces the quantity of vehicles households own. If average *VMT* demand per vehicle is stable in long run, holding anything else constant, more public transit supply will reduce long-run *VMT* demand by cutting the number of vehicles owned. Hence, more investment in public transit system is necessary to suppress the US gasoline demand in long run. Similarly, since a significant effect of *VMT* price on the vehicle quantity decision of household is observed from the results, additional gasoline tax is also expected to reduce gasoline demand by decreasing the vehicle demand in long run.

Vehicle choice behaviors based on annual income levels shown in this model also provide useful information for an alternative environmental tax from an equity point of view. For example, higher income households, according to our results, tend to own new SUVs, which consume more gasoline than Sedan type, and they own more vehicles than other households do.[44] Therefore, an additional sales tax on SUVs or more property tax on vehicles may be recommended if the US government puts heavier weight on the income distribution effect of environmental taxation.

5.2 Vehicle Miles Traveled Demand Model

Parameters in the equation (3.11) are estimated by using the Dubin-McFadden correction term, which is calculated with the estimated probabilities from the vehicle choice model.

In order to analyze household behavior and its relationship with the public transit supply, the total sample is split into two subgroups; one has households in the areas that face higher public transit supply, while the other contains households in areas with lower public transit supply. In addition, an interaction term between *VMT* price and net income is added in each regression to analyze the different responses depending on the income levels within the subgroups. Since our sample has five levels of transit supply indicators, higher public transit supply areas include the highest three indicators, and lower public transit supply areas include the lower two transit indicators, including households in state aggregated MSA of less than 1 million population. There are two reasons. The first reason is that the average transit supply in the state aggregated MSA belong to the lowest level of public transit among other four indicators, thus we have the two lowest levels of public transit indicators. Observations in these groups are more than observations in three higher levels of public transit areas. Second, the total sample is split into five samples based on the five transit indicators, and then the Chow test is used to examine if

[44] Newer SUVs are more environmentally friendly than older ones, but are still no match for the Sedan.

any split sample among the five public transit areas shows any difference from the total sample.

Table 8: Chow Test Results (each split sample based on transit indicators against the total sample)

Chow Test	Null Hypotheses No Difference between the total Sample and each Split sample				
		Split Samples by Public Transit Supply Indicators			
	Transit Supply 1	Public Supply 2	Transit Supply 3	Transit Supply 4	Transit Supply 5
F-stat.	2.60	1.23	1.18	1.38	2.05
Prob. > *F*	0.0000	0.1891	0.2317	0.0894	0.0011

Note: definitions of public transit supply indicators are shown in table A2 in the appendix.

As shown in table 8, at a 10% significant level, *F*-statistics for transit-level 2 and 3 cannot reject the null hypothesis of no difference between the total sample and each transit level sample. Therefore, transit level indicators (1, 2, 3) are grouped as high transit supply, and transit level (4, 5) are grouped as low transit supply.

Table 9 presents the empirical results of regressions using the total sample and two other subgroups; one with high public transit areas, and the other with low public transit areas. Some of the coefficients in each regression differ in magnitude, and yet all of them from three regressions have the same sign except population density where higher population density in the high transit areas significantly decreases *VMT* demand while other two regressions do not show significant negative relation.

The first two variables are the main variables of interest, and it is not difficult to see that an increase in *VMT* price decreases the expected net annual demand for *VMT*, since both *VMT* price and the interaction term have negative signs in all three results. However, it is surprising that the regression with the higher transit sample seems to have the smallest response to the price change, even although the coefficients of *VMT* price and the interaction term are not jointly significant.

Table 9: Results from VMT Demand Model.
Dependent variable: *VMT* – typical miles (robust standard errors in parentheses)

Variables	Total Sample	High Transit [a]	Low Transit [a]
VMT price ($)	-13382.39	-1083.39	-132358.40
	(36635.71)	(41322.83)	(63268.60)
net income ($) x *VMT* price ($)	-0.66	-0.41	-0.40
	(0.30)	(0.37)	(0.54)
net income ($)	0.06	0.02	0.05
	(0.03)	(0.04)	(0.05)
rental cost ($)	-4.11	-3.35	-3.24
	(4.07)	(5.45)	(5.97)
number of household members	-97.90	-169.51	-25.87
	(266.48)	(346.34)	(401.73)
number of drivers in household	-7487.09	-7580.43	-7390.25
	(437.40)	(618.90)	(600.89)
number of household members with jobs	1539.19	1612.25	1422.90
	(285.65)	(409.71)	(375.96)
homeowner	-1083.21	-556.20	-1724.75
	(341.68)	(468.19)	(492.57)
city (urban)	-2786.09	-2400.01	-2969.71
	(380.73)	(673.87)	(451.52)
population density	0.05	-1.28	0.53
	(0.75)	(0.34)	(0.98)
life cycle 1: no children	2975.35	2728.92	3081.07
	(440.11)	(629.10)	(594.65)
life cycle 2: youngest child, age 0-5	4225.24	3646.76	4620.73
	(783.63)	(1107.83)	(1036.58)
life cycle 3: youngest child, age 6-15	3858.09	3295.15	4248.96
	(686.10)	(970.66)	(921.50)
life cycle 4: youngest child, age 16-21	2569.84	2087.95	2819.90
	(1223.00)	(1835.01)	(1483.38)
public transit supply 1 [a]	-2102.02	-	-
	(1446.26)	-	-
public transit supply 2 [a]	-644.75	-	-
	(758.76)	-	-
public transit supply 3 [a]	427.00	-	-
	(534.55)	-	-
public transit supply 4 [a]	490.84	-	-
	(437.12)	-	-
correction	740.30	77.17	1031.51
	(301.87)	418.73	409.03
R^2	0.218	0.220	0.224
number of Observations	19524	6454	13070

Note: [a] Names of CMSA and MSA for cutoffs are shown in the table A2 in the appendix

Due to the complicated variability caused by the interaction, the details of *VMT* price effects on *VMT* net consumption are further investigated at different net income levels and other important mean values in the next subsection.

Some other important variables are transit level indicators in the regression using the total sample. Coefficients on these variables suggest that households in areas that have more public transit supply drive less than in other areas. For the rest of the variables, home-ownership and urban residence decrease *VMT* demand while more workers per household increase the demand. In addition, as expected from the summary statistics, households where the youngest child's age is between 0 and 5 show the highest net demand of *VMT*.

5.3 Short-Run Price Elasticity of Gasoline Demand

Based on the empirical results, the short-run price elasticity of gasoline demand within each income level is calculated, coupled with mean *VMT* price, annual *VMT,* and net income of households. Six sets of the samples are formed into ten deciles so that we can observe the variations across income levels and compare these variations with the previous study.

Table 10 presents the results of the calculations both for all households and for households with vehicles. Our analysis is concentrated on the result including all households rather than only the households with vehicles, since all households must be included when we examine the final income distributional effect of a gasoline tax. The bottom row of the table reports the price elasticity of demand for each sample, using mean values of *VMT* price, annual *VMT* demand, and net income within each sample.

The calculation yields an elasticity of – 0.269 for the total sample regression, which does not deviate from the range of previous studies.[45]

Table 10: Elasticity (bootstrap standard errors in parentheses)

Income Deciles	All Households			Households with Vehicles		
	Total Sample	High Transit	Low Transit	Total Sample	High Transit	Low Transit
1	-0.159	-0.030	-1.289	-0.159	-0.029	-1.290
	(0.286)	(0.362)	(0.636)	(0.332)	(0.417)	(0.649)
2	-0.197	-0.060	-1.205	-0.199	-0.062	-1.205
	(0.317)	(0.350)	(0.433)	(0.318)	(0.324)	(0.512)
3	-0.202	-0.072	-1.038	-0.204	-0.075	-1.038
	(0.257)	(0.285)	(0.432)	(0.265)	(0.263)	(0.393)
4	-0.215	-0.094	-0.895	-0.215	-0.094	-0.895
	(0.232)	(0.308)	(0.372)	(0.209)	(0.251)	(0.369)
5	-0.236	-0.115	-0.840	-0.236	-0.115	-0.840
	(0.212)	(0.230)	(0.333)	(0.208)	(0.269)	(0.353)
6	-0.225	-0.106	-0.769	-0.226	-0.107	-0.769
	(0.174)	(0.192)	(0.319)	(0.175)	(0.209)	(0.291)
7	-0.260	-0.131	-0.781	-0.260	-0.132	-0.782
	(0.181)	(0.222)	(0.303)	(0.164)	(0.229)	(0.293)
8	-0.279	-0.152	-0.701	-0.279	-0.152	-0.701
	(0.149)	(0.194)	(0.225)	(0.143)	(0.171)	(0.251)
9	-0.309	-0.178	-0.640	-0.308	-0.178	-0.640
	(0.127)	(0.157)	(0.216)	(0.128)	(0.175)	(0.219)
10	-0.523	-0.309	-0.769	-0.523	-0.309	-0.769
	(0.193)	(0.204)	(0.327)	(0.177)	(0.245)	(0.359)
Total	-0.269	-0.145	-0.824	-0.284	-0.159	-0.830
	(0.168)	(0.217)	(0.336)	(0.185)	(0.214)	(0.328)

Note: Income Deciles are defined by net income of households.

1: lower than $10,507	2: $10,507 – $16,686
3: $16,686 – $25,693	4: $25,693 – $31,384
5: $31,384 – $36,610	6: $36,610 – $46,227
7: $46,227 – $56,261	8: $56,261 – $75,248
9: $75,248 – $159,062	10: higher than $159,062

[45] Espey (1996) studies the variation in elasticity estimates of gasoline demand. This survey study includes previous estimates with the price elasticity of gasoline demand in the US ranged from – 0.02 to – 1.59. However, this elasticity is much smaller than the result from West (2004)'s that uses the similar method with households data drawn from 1997 CES – that study yields the price elasticity of demand, -0.87.

Comparing the other two subgroups, as expected from the coefficients of the regressions, higher transit supply areas have less elastic demand of gasoline than low transit supply areas. Yet, the elasticity for the high transit supply areas is not significantly supported by the standard errors estimated by the bootstrap method, while the elasticity for the low transit supply areas is significantly supported.

Each column has ten different elasticities based on income levels. Decile 1 indicates the poorest households, and decile 10 indicates the richest households. For the total sample, which is reported in the second column, decile 1 has the smallest elasticity in absolute value, and it increases as the level of income increases. Elasticities for the last three deciles – 8, 9, and 10 – are significant using bootstrap standard errors. The results from the high transit areas are similar, only smaller in absolute value within each decile, but none of these results is significant. Elasticities for the low transit areas show a significantly different variation across the income distribution. The poorest decile has the most elastic demand of gasoline, and the elasticity decreases in absolute value except the richest where the richest decile shows more elastic demand than second and third highest decile. All of estimated elasticities for low transit areas are significant at 5% significance level.

These empirical results support an assumption, suggested by Kayser (2000), that responses of the household in the short-run are more affected by the use of private driving as a necessity than by cheap gasoline prices in the US. It is likely that necessary demand for annual *VMT* is fixed based on the long-run decision of the household, and is not affected relatively by price changes, while the rest of driving purposes such as leisure are flexible and affected by price changes. The decision might include the structure of residential areas, location of the house, place of work, accessibility to public transportation, etc. For example, households would decide whether to own a car based on their environment such as how close the nearest available bus station is, and the distance they must drive to work. Once they have made these long-run decisions, a small increase in gasoline price would not affect their necessary demand in a significant way, but only affects their leisure purpose driving.

In high transit supply areas, the poorest households must have strong reasons, such as going to work and school, to demand fixed distance of annual *VMT* when they decide to own vehicles because they have other alternatives such as buses and subways. Nevertheless, their annual *VMT* is much smaller than the richer households'. This is consistent with that they have little room for unnecessary-purpose demand to respond to the price changes. On the other hand, it is likely that greater portions of annual *VMT* for the rich in high transit areas are not necessities because they have enough leisure-purpose miles to respond. For those in lower transit areas, both poor and rich do not have any other alternative. Therefore, even poor households in these areas have other unnecessary purposes for private driving such as vacation and shopping, which they would have to give up for lower expenditure on gasoline.

For households in the total sample, since our sample excludes households in rural areas, which do not have public transit system at all, the results from the total sample represent the households who might face higher public transit supply than the US average. It is not strange that the households in total sample show the behavior that is more similar to the households in high transit supply areas rather than households in low transit supply areas. By the same reason, the income distributional effect of a gasoline tax, which is the main issue that we are interested in, also apply to households in higher transit supply than the US average.

In order to confirm this assumption, a further investigation on the purposes of private driving based on annual income level of households is required. However, our study cannot proceed any further due to data limitations. As discussed earlier in the paper, we do not have data that identifies purposes of each *VMT* demand. Instead, this assumption may be supported implicitly by analyses of occupation heterogeneity among different income level households in each residential area. In particular, information on proportion of self-employers among poor households or rich households in each area may enforce our conclusion. Unfortunately, our dataset does not have such detailed occupational information.

5.4 Distributional Effects

The distributional effects of a gasoline tax are analyzed using two measurements of tax burdens; one is a percentage of the predicted additional gasoline tax paid in households' annual income, and the other is a percentage of the predicted consumer surplus change in households' annual income, which households would lose due to an additional gasoline tax. These burdens are calculated with estimated elasticities and a hypothetical additional gasoline tax, 3 cents per mile, holding everything else constant. A linear *VMT* demand curve is also assumed to calculate the predicted consumer surplus loss.[46]

[46] Our study follows the simulation of West (2004). In her study, the optimal gasoline tax is assumed to be an additional 2 cents per mile based on Parry and Small (2005). Parry and Small (2005) suggest that the optimal gasoline tax for the US is $1.01 per gallon. Since average gasoline tax in the US in 2001 was

Table 11: Tax Burdens (as a percentage)

Income Deciles	All Households				Households with Vehicles	
	Constant Demand Elasticity		Varying in Elasticity		Varying in Elasticity	
	$\frac{\Delta Tax}{Income}$	$\frac{\Delta CS}{Income}$	$\frac{\Delta Tax}{Income}$	$\frac{\Delta CS}{Income}$	$\frac{\Delta Tax}{Income}$	$\frac{\Delta CS}{Income}$
1	2.098	2.335	2.291	2.432	5.115	5.257
2	1.751	1.851	1.804	1.878	2.174	2.247
3	1.244	1.323	1.284	1.342	1.696	1.755
4	1.289	1.353	1.315	1.366	1.453	1.505
5	1.156	1.209	1.169	1.216	1.216	1.263
6	1.076	1.129	1.094	1.138	1.197	1.241
7	0.939	0.982	0.941	0.983	0.986	1.027
8	0.852	0.890	0.849	0.888	0.879	0.918
9	0.730	0.762	0.721	0.758	0.738	0.775
10	0.394	0.411	0.361	0.395	0.381	0.415
Suits Index	-0.245	-0.248	-0.264	-0.257	-0.289	-0.281

Note: Income Deciles are defined by net income of households.

1: lower than \$10,507 2: \$10,507 – \$16,686
3: \$16,686 – \$25,693 4: \$25,693 – \$31,384
5: \$31,384 – \$36,610 6: \$36,610 – \$46,227
7: \$46,227 – \$56,261 8: \$56,261 – \$75,248
9: \$75,248 – \$159,062 10: higher than \$159,062

Table 11 presents the results of the calculations for all households and households with vehicles. For the all households sample, tax burdens are calculated on two assumptions in order to observe how the responses of households affect the distributional effects. One assumption is that the price elasticity of demand is constant on all income levels (second and third column) and the other assumption is that the price elasticity

37.11 cents per gallon, additional gasoline tax should be 63.89 cents to obtain the optimal tax that Parry and Small suggest. Therefore, approximately 3 cents per mile is finally assumed when the average MPG in our sample, 22 miles per gallon is applied.

varies across the income levels (fourth and fifth column). The bottom row of the table reports the Suits Index for each sample to compare the degree of regressivity.[47]

For each case in eight different columns, decile 1 has the heaviest tax burden while decile 10 has the lightest tax burden, and the tax burden decreases as households' level of annual income increases. This means that the hypothetical optimal gasoline tax is significantly regressive overall.

The degrees of regressivity in each sample are different. The additional tax is less regressive when all households are included in the sample because lower deciles include more non-vehicle households who cannot bear any gasoline tax burden. Among all households, the tax is more regressive when we allow households to respond to the tax differently based on their income levels. The Suits Index also confirms these results for each degree of regressivity. By allowing households to respond to the additional gasoline tax differently based on their income levels, the Suits Index for additional tax paid falls from -0.245 to -0.264, and from -0.248 to -0.257 for the additional consumer surplus loss. An addition gasoline tax is expected to make the income distribution more regressive.

Due to different data and assumptions, degrees of the Suits Index in our study are not necessarily comparable to others. However, when those data and assumption differences are ignored, overall regressivity of a gasoline tax seems to be pretty high in our study compared to a previous study – West (2004) has a Suits Index of -0.153, and also compared to average federal excise – Roach (2003) has an average Suits Index of

[47] Suits (1977) suggests the index. The index measures the degrees of progressivity or regressivity for any given tax. The index varies from +1 to -1. A positive index indicates the tax is progressive while a negative index means regressive.

-0.215 for average federal excise tax in 2000 and 2001. As discussed already, using the annual income of household as a proxy for well-being makes it more regressive than when viewed from a lifetime perspective, and different responses of households to the tax change across income levels also enforces its regressivity.

6. Conclusion

This study investigates the distributional effects of a gasoline tax. The study focuses on analyzing how the public transit system, which is considered an alternative to private driving influences the distributional effects, in particular for poor households. To analyze the effect of public transit system, the total household sample is split into two subgroups, one living in the areas with higher levels of public transit supply, and the other living in the areas with lower levels of public transit supply. Price elasticities of gasoline demand are then estimated based on the sample areas.

Methodologically, the study adopts the Dubin-McFadden correction method, modified by West (2004). This framework enables us to correct the bias caused by the interrelated decisions between choosing vehicles and consuming gasoline. Two sub-models are estimated: the household vehicle choice model and the household Vehicle Miles Traveled (*VMT*) demand model. The estimated probabilities from the first step are used to correct the bias in the *VMT* demand model.

The primary household data for the empirical analysis is drawn from the 2001 National Household Travel Survey (NHTS), and merged with additional information on residential areas and vehicles, which include gasoline prices, used car prices, and annual service miles of public transit.

As a result, different responses are observed based on the supply of the public transits. Higher transit supply areas have less elastic demand than low transit supply areas. For different responses within income levels, the poorest have the smallest elasticity in absolute value, and this increases as income level increases in high transit supply areas, and this relationship displays the opposite tendency in the low transit supply areas. The total sample, which excludes households in rural areas, also shows similar behavior from the households in high transit supply areas. Therefore, based on this result, it is assumed that the price elasticity of gasoline demand in the short-run is affected more by the use of private driving as a necessity than it is by the gasoline price. A larger proportion of driving purposes are a necessity for poorer households while annual demand is much smaller than it is for the rich households. Therefore, the hypothetical optimal gasoline tax becomes more regressive across all income levels after reflecting household behavior to the price of gasoline.

The results, nevertheless, suggest further investigations into several specific topics. First, heterogeneous behaviors of households within income levels in each area should be analyzed further. In this study, responses of the households in the short-run are likely to be more affected by the use of private driving as a necessity than cheap gasoline prices. Therefore, a detailed examination into the different *VMT* demands for each purpose of private driving would potentially provide strong evidence to confirm our results if such data is available. Otherwise, alternative analyses, for example, a study of occupation heterogeneity that includes self-employers among different income level households in each area may implicitly provide a good evidence to support our conclusion.

Second, detailed long run decisions on public transit use should be studied further. In particular, the specific housing location and vehicle buying decision based on the public transit supply may explain when and how households use public transit instead of their own vehicles. Although our study shows that public transit is not used as a good substitute for private driving in short-run, but it does not means that it is not a good substitute for the private driving in long run. Furthermore, a result from the households vehicle choice model shows that an increase in public transit supply decreases the households' tendency to own vehicles and that the reduced number of vehicles helps to reduce total *VMT* demand in long run. This implies that public transit in long run is a good substitute for private driving, thus, investment in public transit system must be increased to reduce the huge demand of gasoline in the U.S.

Although our study has several limitations, it still gives us a nice picture of the income distribution effects of a gasoline tax. In general, a gasoline tax is regressive across all income levels. Excluding households in rural areas, the household behavior based on their income levels makes the gasoline tax more regressive when an additional gasoline tax is imposed. If the government cares about equity more than efficiency for these households then the gasoline tax would not be the best choice. To control the gasoline demand and protect the environment, it is recommended that the government consider other alternatives such as a tax on gas-guzzling luxury SUVs, which are usually purchased by the rich. Similarly, a property tax on vehicles will also be effective since a high-income household tends to own more vehicles.

REFERENCES

Archibald, Robert and Robert Gillingham, "An Analysis of the Short-Run Consumer Demand for Gasoline Using Household Survey Data," *The Review of Economics and Statistics*, Vol. 62, No. 4. (1980): 622-628

Baum-Snow, Nathaniel and Matthew E. Kahn, "The Effects of New Public Projects to Expand Urban Rail Transit," *Journal of Public Economics*, 77, (2000): 241-263

Bento, Antonio M., Lawrence H. Goulder, Emeric Henry, Mark R. Jacobsen, and Roger H. von Haefen, "Distributional and Efficiency Impacts of Gasoline Taxes: An Econometrically-Based Multi-Market Study," *American Economic Review*, Vol. 95, No 2, May (2005): 282-287

Bento, Antonio M., Maureen L. Cropper, Ahmed Mushfiq Mobarak, and Katja Vinha, "The Impact of Urban Spatial Structure on Travel Demand In the United States," *the World Bank Policy Research Working Paper No. 3007*, March (2003).

Berkowitz, Michael K., Nancy T. Gallini, Eric J. Miller, and Robert A. Wolfe, "Disaggregate Analysis of the Demand for Gasoline," *The Canadian Journal of Economics*, Vol. 23, No. 2, May (1990): 253-275

Caspersen, Erik and Gilbert Metcalf, "Is a Value Added Tax Regressive? Annual Versus Lifetime Incidence Measures," *National Tax Journal*, Vol. 47, No. 4, December, (1994): 731-746

Corlett, W. J. and D.C. Hague, "Complementarity and the Excess Burden of Taxation," *The Review of Economic Studies*, Vol. 21, No. 1, (1953 - 1954): 21-30

Dahl, Carol A., "Demand for Transportation Fuels: A Survey of Demand Elasticities and Their Components," *The Journal of Energy Literature*, Vol. 1, No. 2, (1995): 3-27

Dahl, Carol A. and Thomas Sterner, "A Survey of Econometric Gasoline Demand Elasticities," *International Journal of Energy Systems*, Vol. 11, No. 2, January (1991a): 53-76

Dahl, Carol A. and Thomas Sterner, "Analyzing Gasoline Demand Elasticities: A Survey," *Energy Economics* 13(3) July (1991b): 203-10

Deaton, Angus and John Muellbauer, "An Almost Ideal Demand System," *American Economic Review*, Vol. 70, No. 3, June (1980): 312-326

Dubin, Jeffrey A., Daniel L. McFadden, "An Econometric Analysis of Residential Electric Appliance Holding and Consumption," *Econometrica*, Vol. 52, No. 2, March (1984): 345-362

Espey, Molly, "Explaining The Variation in Elasticity Estimates of Gasoline Demand in the United States: A Meta-Analysis," *Energy Journal*, Vol. 17, Issue 3 (1996)

Feng, Ye, Don Fullerton and Li Gan, "Vehicle Choices, Miles Driven and Pollution Policies," *NBER Working Paper*, No. 11553, March (2005).

Goldberg, Pinelopi Koujianou, "The Effects of the Corporate Average Fuel Efficiency Standards in the US," *The Journal of Industrial Economics*, Vol. 46, No.1, March (1998): 1-33

Goulder, Lawrence H. and Roberton C. Williams III, "The Substantial Bias from Ignoring General Equilibrium Effects in Estimating Excess Burden, and a Practical Solution," *Journal of Political Economy*, Vol. 111, Issue 4, August (2003): 898-927

Graham, Daniel J. and Stephen Glaister, "The Demand for Automobile Fuel: A Survey of Elasticities," *Journal of Transport Economics and Policy*, Vol. 36, Part 1, January (2002): 1-26

Greening, Lorna A., Hann Tarn Jeng, John P. Formby and David C. Cheng, "Use of region, life-cycle and role variables in the short-run estimation of the demand for gasoline and miles travelled," *Applied Economics*, 27 (1995): 643-656

Harrington, Winston and Virginia McConnell, "Motor Vehicles and the Environment," RFF Report, Resources for the future, Washington, D.C. April (2003)

Kayser, Hilke A., "Gasoline Demand and Car Choice: Estimating Gasoline Demand Using Household Information," *Energy Economics*, Vol. 22, Issue 3, June (2000): 331-348

Madden, David, "Labour Supply, Commodity Demand and Marginal Tax Reform," *The Economic Journal*, Vol. 105, No. 429, March (1995): 485-497

Mannering, Fred, and Clifford Winston, "A Dynamic Empirical Analysis of Household Vehicle Ownership and Utilization," *The RAND Journal of Economics*, Vol. 16, No. 2, Summer (1985): 215-236

McFadden, Daniel L., "The Measurement of Urban Travel Demand," *Journal of Public Economics* 3, (1974): 303-328

McFadden, Daniel L., “Conditional Logit Analysis of Qualitative Choice Analysis,” in *Frontiers in Econometrics*, ed. P. Azrembka. New Nork: Academic Press, (1974): 105-142

McFadden, Daniel L., “Modelling the Choice of Residential Location,” in *Spatial Interaction Theory and Planning Models*, ed. A. Karlquist et al., Amsterdam: North-Holland Publishing Company, (1978).

Metcalf, Gilbert E., “The National Sales Tax: Who Bears the Burden?” *Cato Policy Analysis No. 289*, Washington, DC: Cato Institute, Dec. 8, (1997).

Parry, Ian W.H. and Kenneth A. Small, “Does Britain or the United States Have the Right Gasoline Tax?” *American Economic Review*, Vol. 95, No. 4, September (2005): 1276-1289

Panel Study of Income Dynamics, (Family) public use dataset. Produced and distributed by the University of Michigan with primary funding from the National Science Foundation, the National Institute of Aging, and the National Institute of Child Health and Human Development. Ann Arbor, MI, (2001).

Poterba, James M., “Lifetime Incidence and the Distributional Burden of Excise Taxes,” *American Economic Review*, Vol. 79, No. 2, May (1989): 325-330

Poterba, James M., “Is the Gasoline Tax Regressive?” in *Tax Policy and the Economy*, Vol. 5. ed. Bradford, D., MIT Press, Boston, (1991): 145-164

Ramsey, F. P., “A Contribution to the Theory of Taxation,” *The Economic Journal*, Vol. 37, No. 145, March (1927): 47-61

Roach, Brian, **“**Progressive and Regressive Taxation in the United States: Who's Really Paying (and Not Paying) their Fair Share?**”** *GDAE Working Paper* No. 03-10, October (2003).

Sipes, Kristin N. and Robert Mendelsohn, “The Effectiveness of Gasoline Taxation to Manage Air Pollution,” *Ecological Economics*, Vol. 36, No. 2, (2001): 299-309

Suits, Daniel B., “Measurement of Tax Progressivity,” *American Economic Review*, Vol. 67, No. 4, September (1977): 747-752

Train, Kenneth, “Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand,” Cambridge, Massachusetts: The MIT Press (1986)

U.S. Department of Transportation, Bureau of Transportation Statistics, “National Transportation Statistics 2002,” BTS02-08, Washington, DC, U.S. Government Printing Office, December (2002).

Walls, Margaret and Jean Hanson, “Distributional Aspects of an Environmental Tax Shift: The Case of Motor Vehicle Emissions Taxes,” *National Tax Journal*, Vol. 52, No. 1, March (1999): 53-65

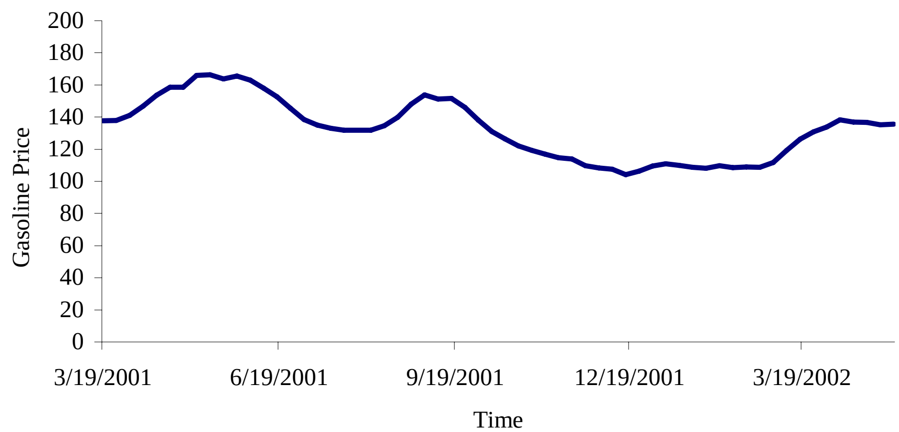
West, Sarah E., “Distribution effects of alternative vehicle pollution control policies,” *Journal of Public Economics*, 88 (2004): 735-575

West, Sarah E. and Roberton C. Williams III, “Empirical Estimates for Environmental Policy Making in a Second-Best Setting,” *NBER Working Paper*, No. 10330, March (2004).

APPENDIX

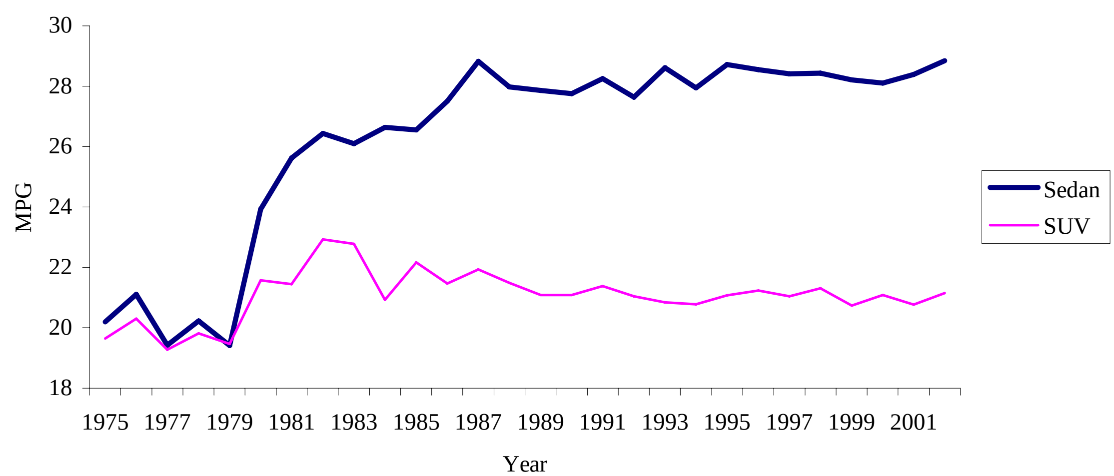
1. Data

Figure A1: U.S. Regular Conventional Retail Gasoline Prices (03/2001 – 05/2002) [a]
(Cents per Gallon)



[a] The source of the retail gasoline prices: U.S. Department of Energy, Energy Information Administration. (Mean: €132.47, Standard Deviation: 18.43)

Figure A2: Average MPG for Sedans and SUVs [a]



[a] Sedans and SUVs in our study indicate passenger cars, and light trucks such as pickup trucks and SUVs.

Table A1: Vehicle Choice Structure and Averages of Main Variables

Note: The vehicle choice portfolios are classified into 16 nested groups, depending on the number of vehicles per household, vehicle types, and vintage. The first nest is classified by the number of vehicles, (0, 1, 2). Then, within each number of vehicles, the second nest is classified by the combinations of the vehicle type and vintage. The vehicles are classified into two types, (Sedan, SUV). Along with the vehicle type, the vehicles are classified into three different vintage choices, (New, Medium, Old): New includes the vehicles newer than 1996; Medium vehicles are those between 1989 and 1996; and Old vehicles are older than 1989. For two vehicle households, we set vintage to that of the newer vehicle.

First Nest	Second Nest		Portfolio Numbers	Averages in Each Portfolio		
Number of Cars	Vehicle Types	Vintages		*VMT*	Used Car Price	MPG
1	Sedan	New	1	10,994	7,966	25.94
		Medium	2	8,885	2,501	25.45
		Old	3	6,397	819	24.32
	SUV	New	4	13,449	9,680	19.94
		Medium	5	11,708	2,566	19.42
		Old	6	10,585	757	20.26
2	Sedan, Sedan	New	7	23,176	13,390	26.13
		Medium	8	19,566	4,609	25.43
		Old	9	17,174	1,596	24.18
	Sedan, SUV	New	10	24,882	15,307	22.52
		Medium	11	19,471	4,599	22.11
		Old	12	14,749	1,595	21.92
	SUV, SUV	New	13	26,987	16,098	19.30
		Medium	14	20,952	4,850	19.10
		Old	15	16,546	1,469	19.68
0	N/A	N/A	16	0	0	0.00

Table A2: Total Public Transportation Annual Service Miles Driven

Note: Households in the total sample are separated into two groups. One group includes households who belong to CMSA and MSA areas identified by 2001 NHTS, and the other group includes households living in MSA areas of less population than 1 million. The latter group is not identified by names of MSA, but instead, is aggregated by state level in 2001 NHTS. Households in identified CMSA and MSA areas are split into four levels with the approximately same proportion of observations based on their public transit supply. State aggregated households in MSA areas of less than 1 million in size are treated as one indicator variable. As a result, five levels of transit supply indicators are created.

High Transit Supply Areas

Classification		Rank	CMSA, MSA Level	Service Miles Per Square Mile
High Transit Supply Areas	Tran 1	1	New York--Northern New Jersey--Long Island, NY--NJ--CT--PA	31503
	Tran 2	2	Philadelphia--Wilmington--Atlantic City, PA--NJ--DE--MD	25102
		3	Miami--Fort Lauderdale, FL	23074
		4	San Francisco--Oakland--San Jose, CA	21202
		5	Providence--Fall River--Warwick, RI--MI	18708
		6	Chicago--Gary--Kenosha, IL--IN--WI	16400
		7	Honolulu, HI (entire Oahu Island)	13809
		8	Seattle--Tacoma--Bremerton, WA	13584
	Tran 3	9	Pittsburgh, PA	12308
		10	Boston--Worcester--Lawrence, MA--NH--ME--CT	10735
		11	San Diego, CA	10639
		12	Washington--Baltimore, DC--MD--VA--WV	10016
		13	Hartford, CT	9988
		14	San Antonio, TX	9447
		15	Minneapolis--St. Paul, MN--WI	8426
		16	Houston--Galveston--Brazoria, TX	8244
		17	Milwaukee--Racine, WI	8178
		18	Los Angeles--Riverside--Orange County, CA	8175
		19	Detroit--Ann Arbor--Flint, MI	7769
		20	Atlanta, GA	7595
		21	Buffalo--Niagara falls, NY	7357
		22	Cleveland--Akron, OH	6818
		23	Denver--Boulder--Greeley, CO	6536
		24	Portland--Salem, OR--WI	6468

Table A2: Total Public Transportation Annual Service Miles Driven (Continued)

Note: Households in the total sample are separated into two groups. One group includes households who belong to CMSA and MSA areas identified by 2001 NHTS, and the other group includes households living in MSA areas of less population than 1 million. The latter group is not identified by names of MSA, but instead, is aggregated by state level in 2001 NHTS. Households in identified CMSA and MSA areas are split into four levels with the approximately same proportion of observations based on their public transit supply. State aggregated households in MSA areas of less than 1 million in size are treated as one indicator variable. As a result, five levels of transit supply indicators are created.

Low Transit Supply Areas

Classification		Rank	CMSA, MSA Level	Service Miles Per Square Mile
Low Transit Supply Areas	Tran 4	25	Dallas--Fort Worth, TX	6419
		26	Orlando, FL	6318
		27	Tampa--St. Petersburg--Clearwater, FL	6142
		28	Cincinnati--Hamilton, OH--KY--IN	6124
		29	Louisville, KY--IN	5988
		30	St. Louis, MO	5287
		31	Jacksonville, FL	5017
		32	Austin--San Marcos, TX	4843
		33	Columbus, OH	4453
		34	Norfolk--Virginia Beach--Newport News, VA--NC	4140
		35	Charlotte--Gastonia--Rock Hill, NC--SC	3967
		36	Memphis, TN--AR--MS	3458
		37	Sacramento--Yolo, CA	3086
		38	Indianapolis, IN	3071
		39	Raleigh--Durham--Chapel Hill, NC	2928
		40	Salt Lake City--Ogden, UT	2922
		41	Kansas City, MO--KS	2830
		42	Rochester, NY	2720
		43	New Orleans, LA	2421
		44	Phoenix--Mesa, AZ	2380
		45	Grand Rapids--Muskegon--Holland, MI	1388
		46	Nashville, TN	1381
		47	Greensboro--Winston-Salem--High Point, NC	1273
		48	Oklahoma City, OK	1127
		49	Las Vegas, NV--AZ	621
	Tran 5		suppressed, in an MSA of less than 1 million	1464

2. Estimation Results

Table A3: Definitions of Variables in Nested Logit Model

Names	Definitions
one	1 if a household owns one vehicle
two	1 if a household owns two vehicles
worker	number of household members with jobs
homeowner	1 if a household is a homeowner
income	total household income last 12 months ($)
TR	public transit supply
density	population density for each MSA area
rentalcost	rental cost
AOC	Annual Operating Cost
*vmt*price	*VMT* price per mile
portfolio1-16	1 if the household vehicle choice belongs to the portfolio (1-16)
income1	1 if household's annual income is lower than $17,500
income2	1 if household's annual income is between $17,500 and $32,500
income3	1 if household's annual income is between $32,500 and $47,500
income4	1 if household's annual income is between is $47,500 and $72,500
income5	1 if household's annual income is higher than $72,500
tran1	1 if households in MSA with transit supply is greater than 28,000
tran2	1 if households in MSA with transit supply is between 28,000 and 13,000
tran3	1 if households in MSA with transit supply is between 13,000 and 6,450
tran4	1 if households in MSA with transit supply is lesser than 6,450
tran5	1 if households in MSA of less than 1 million, which has average transit supply of 1,464
life1	1 if household has no children
life2	1 if household has youngest child 0-5
life3	1 if household has youngest child 6-15
life4	1 if household has youngest child 16-21
life5	1 if household is retired, no child
hhsize	number of households
drvrcnt	number of drivers in household
white	1 if a respondent is white
city	1 if a household lives in urban area
subway	1 if a household in MSA with rail (subway)

Table A4: Full Results of Vehicle Choice Model (Nested Logit Model)
Definitions of variables are shown in A3 in the previous page

Note: number of observations is 399,264; number of households used is 24,954
log likelihood = - 46092.069; χ^2 = 46190.22
LR test of homoskedasticity (iv = 1): χ^2 = 2558.38 support the nested logit model.

First Nest
< Number of Vehicles >

Variable	Coef.	Std. Err.
one*worker	0.30282	0.03784
one*homeowner	1.73226	0.04965
one*income	0.00003	0.00000
one*TR	-0.00013	0.00001
one*density	0.00197	0.00014
two*worker	0.47718	0.05231
two*homeowner	2.38282	0.06766
two*income	-0.00002	0.00000
two*TR	-0.00020	0.00001
two*density	0.00020	0.00020
(incl.valueparameters)		
/OneCar	0.37975	0.01633
/TwoCar	2.88793	0.15839

Second Nest
< Vintage and Type >

Variable	Coef.	Std. Err.
Rentalcost	0.00326	0.00007
AnnualOperatingCost	0.00438	0.00013
*VMT*price	-117.96620	2.39558
Portfolio2*income2	-0.54526	0.06953
Portfolio3*income2	-0.98245	0.09435
Portfolio4*income2	0.05423	0.09947
Portfolio5*income2	-0.35286	0.10795
Portfolio6*income2	-0.88375	0.18322
Portfolio7*income2	-0.04149	0.07546
Portfolio8*income2	0.22507	0.13126
Portfolio9*income2	-0.26000	0.31913
Portfolio10*income2	-0.00487	0.06284
Portfolio11*income2	0.86256	0.13055
Portfolio12*income2	-0.52769	0.31871
Portfolio13*income2	0.02453	0.11294
Portfolio14*income2	0.36093	0.21644
Portfolio2*income3	-0.95437	0.07897
Portfolio3*income3	-1.76952	0.12672
Portfolio4*income3	0.33503	0.10308
Portfolio5*income3	-0.71295	0.12092
Portfolio6*income3	-1.18886	0.21388
Portfolio7*income3	0.17231	0.07324
Portfolio8*income3	0.22527	0.12737
Portfolio9*income3	-0.82675	0.33792
Portfolio10*income3	0.34597	0.06082

Variable	Coef.	Std. Err.
Portfolio11*income3	0.75486	0.12927
Portfolio12*income3	-0.93956	0.32139
Portfolio13*income3	0.29015	0.10498
Portfolio14*income3	0.10408	0.21321
Portfolio2*income4	-1.28211	0.09562
Portfolio3*income4	-1.93674	0.15950
Portfolio4*income4	0.33620	0.11412
Portfolio5*income4	-0.92608	0.14059
Portfolio6*income4	-1.59233	0.28319
Portfolio7*income4	0.36840	0.07771
Portfolio8*income4	0.05227	0.13371
Portfolio9*income4	-1.73672	0.43486
Portfolio10*income4	0.64066	0.06550
Portfolio11*income4	0.38233	0.13645
Portfolio12*income4	-1.62475	0.37821
Portfolio13*income4	0.67124	0.10521
Portfolio14*income4	-0.13940	0.21998
Portfolio2*income5	-1.39753	0.11041
Portfolio3*income5	-1.67424	0.17502
Portfolio4*income5	0.08598	0.12667
Portfolio5*income5	-1.88435	0.19669
Portfolio6*income5	-2.69875	0.52701
Portfolio7*income5	0.72190	0.09103
Portfolio8*income5	-0.08358	0.14863
Portfolio9*income5	-1.54093	0.41945
Portfolio10*income5	0.88305	0.08004
Portfolio11*income5	0.09878	0.15039
Portfolio12*income5	-3.38400	0.75539
Portfolio13*income5	0.77997	0.11513
Portfolio14*income5	-0.68738	0.24551
Portfolio2*TransitLevel1	-0.19991	0.15348
Portfolio3*TransitLevel1	-0.01164	0.22639
Portfolio4*TransitLevel1	-1.24498	0.19745
Portfolio5*TransitLevel1	-0.82075	0.25474
Portfolio6*TransitLevel1	-0.66613	0.44735
Portfolio7*TransitLevel1	1.84486	0.17110
Portfolio8*TransitLevel1	1.38677	0.24033
Portfolio9*TransitLevel1	1.17706	0.62036
Portfolio10*TransitLevel1	1.04235	0.16275
Portfolio11*TransitLevel1	1.13664	0.23403
Portfolio12*TransitLevel1	1.38365	0.77085
Portfolio13*TransitLevel1	1.07876	0.20189
Portfolio14*TransitLevel1	1.30986	0.43268
Portfolio2*TransitLevel2	-0.13554	0.13752
Portfolio3*TransitLevel2	-0.07270	0.20278

Table A4: Continued

Variable	Coef.	Std. Err.
Portfolio4*TransitLevel2	-0.84604	0.18377
Portfolio5*TransitLevel2	-0.64682	0.23543
Portfolio6*TransitLevel2	-0.35658	0.40117
Portfolio7*TransitLevel2	0.97967	0.10920
Portfolio8*TransitLevel2	0.58928	0.18895
Portfolio9*TransitLevel2	0.64753	0.56324
Portfolio10*TransitLevel2	0.50755	0.09859
Portfolio11*TransitLevel2	0.68603	0.17199
Portfolio12*TransitLevel2	0.72297	0.66397
Portfolio13*TransitLevel2	0.64203	0.14094
Portfolio14*TransitLevel2	0.82607	0.33181
Portfolio2*TransitLevel3	0.07389	0.09164
Portfolio3*TransitLevel3	0.14355	0.13260
Portfolio4*TransitLevel3	-0.18881	0.11446
Portfolio5*TransitLevel3	-0.00988	0.13992
Portfolio6*TransitLevel3	0.04990	0.24940
Portfolio7*TransitLevel3	0.51003	0.06805
Portfolio8*TransitLevel3	0.53994	0.11777
Portfolio9*TransitLevel3	0.67637	0.42577
Portfolio10*TransitLevel3	0.29842	0.05456
Portfolio11*TransitLevel3	0.32334	0.10541
Portfolio12*TransitLevel3	0.24311	0.41918
Portfolio13*TransitLevel3	0.27963	0.08403
Portfolio14*TransitLevel3	0.50566	0.18856
Portfolio2*TransitLevel4	0.03271	0.08163
Portfolio3*TransitLevel4	-0.11059	0.12312
Portfolio4*TransitLevel4	-0.17087	0.09988
Portfolio5*TransitLevel4	-0.15496	0.12733
Portfolio6*TransitLevel4	-0.48256	0.25993
Portfolio7*TransitLevel4	0.31082	0.05729
Portfolio8*TransitLevel4	0.45516	0.10052
Portfolio9*TransitLevel4	0.58505	0.36503
Portfolio10*TransitLevel4	0.11839	0.04282
Portfolio11*TransitLevel4	0.20673	0.08972
Portfolio12*TransitLevel4	0.22522	0.34620
Portfolio13*TransitLevel4	0.14583	0.06972
Portfolio14*TransitLevel4	0.51976	0.15020
Portfolio2*LifeCycle1	0.50107	0.05802
Portfolio3*LifeCycle1	0.32039	0.08510
Portfolio4*LifeCycle1	0.42495	0.07398
Portfolio5*LifeCycle1	1.27708	0.09899
Portfolio6*LifeCycle1	1.01056	0.16774
Portfolio7*LifeCycle1	-0.13085	0.04579
Portfolio8*LifeCycle1	0.45404	0.08948
Portfolio9*LifeCycle1	0.14767	0.29373
Portfolio10*LifeCycle1	0.01133	0.03917
Portfolio11*LifeCycle1	0.80700	0.08850
Portfolio12*LifeCycle1	1.27468	0.33835
Portfolio13*LifeCycle1	0.02970	0.07366
Portfolio14*LifeCycle1	1.47002	0.19876
Portfolio2*LifeCycle2	0.66086	0.14303
Portfolio3*LifeCycle2	0.45031	0.20236
Portfolio4*LifeCycle2	0.86051	0.16424

Variable	Coef.	Std. Err.
Portfolio5*LifeCycle2	1.01900	0.20395
Portfolio6*LifeCycle2	0.44080	0.40625
Portfolio7*LifeCycle2	0.23752	0.09221
Portfolio8*LifeCycle2	0.31565	0.16167
Portfolio9*LifeCycle2	-0.55665	0.52712
Portfolio10*LifeCycle2	0.25069	0.06036
Portfolio11*LifeCycle2	0.34708	0.13195
Portfolio12*LifeCycle2	0.45853	0.50492
Portfolio13*LifeCycle2	0.47375	0.09740
Portfolio14*LifeCycle2	0.77466	0.27085
Portfolio2*LifeCycle3	0.62951	0.12479
Portfolio3*LifeCycle3	0.31061	0.18241
Portfolio4*LifeCycle3	0.89851	0.14003
Portfolio5*LifeCycle3	1.29610	0.17249
Portfolio6*LifeCycle3	0.94771	0.32570
Portfolio7*LifeCycle3	0.09220	0.08844
Portfolio8*LifeCycle3	0.09973	0.15570
Portfolio9*LifeCycle3	0.20767	0.44093
Portfolio10*LifeCycle3	0.13116	0.05727
Portfolio11*LifeCycle3	0.43012	0.12312
Portfolio12*LifeCycle3	0.62271	0.46714
Portfolio13*LifeCycle3	0.47374	0.09197
Portfolio14*LifeCycle3	1.17976	0.24962
Portfolio2*LifeCycle4	0.12850	0.18893
Portfolio3*LifeCycle4	0.37359	0.25970
Portfolio4*LifeCycle4	0.20395	0.23878
Portfolio5*LifeCycle4	0.92712	0.26286
Portfolio6*LifeCycle4	0.85577	0.46809
Portfolio7*LifeCycle4	-0.04477	0.09858
Portfolio8*LifeCycle4	-0.00732	0.18077
Portfolio9*LifeCycle4	-0.52149	0.75342
Portfolio10*LifeCycle4	-0.37048	0.09337
Portfolio11*LifeCycle4	0.12617	0.17707
Portfolio12*LifeCycle4	0.77602	0.78346
Portfolio13*LifeCycle4	-0.04129	0.16245
Portfolio14*LifeCycle4	0.58768	0.39621
Portfolio2*HouseholdSize	-0.02735	0.04773
Portfolio3*HouseholdSize	0.06235	0.06323
Portfolio4*HouseholdSize	0.09414	0.05339
Portfolio5*HouseholdSize	0.34736	0.05930
Portfolio6*HouseholdSize	0.20000	0.11063
Portfolio7*HouseholdSize	-0.41515	0.04152
Portfolio8*HouseholdSize	-0.09833	0.06202
Portfolio9*HouseholdSize	0.19329	0.15040
Portfolio10*HouseholdSize	0.04488	0.02113
Portfolio11*HouseholdSize	0.27412	0.03860
Portfolio12*HouseholdSize	0.39605	0.10654
Portfolio13*HouseholdSize	0.19040	0.02940
Portfolio14*HouseholdSize	0.37433	0.06358
Portfolio2*DriverCount	1.08646	0.06351
Portfolio3*DriverCount	1.00826	0.08937
Portfolio4*DriverCount	-0.57004	0.07784
Portfolio5*DriverCount	0.27134	0.08749

Table A4: Continued

Variable	Coef.	Std. Err.	Variable	Coef.	Std. Err.
Portfolio6*DriverCount	0.47465	0.16351	Portfolio4*Urban	-0.80508	0.07236
Portfolio7*DriverCount	-1.53858	0.07455	Portfolio5*Urban	-0.33330	0.09434
Portfolio8*DriverCount	-0.79954	0.08881	Portfolio6*Urban	-0.44138	0.16529
Portfolio9*DriverCount	-1.28488	0.22513	Portfolio7*Urban	0.08339	0.04473
Portfolio10*DriverCount	-2.20705	0.06988	Portfolio8*Urban	0.64306	0.09783
Portfolio11*DriverCount	-1.37514	0.07180	Portfolio9*Urban	0.77351	0.33540
Portfolio12*DriverCount	-1.90155	0.20306	Portfolio10*Urban	-0.25928	0.03189
Portfolio13*DriverCount	-2.85944	0.08605	Portfolio11*Urban	0.05254	0.07020
Portfolio14*DriverCount	-1.88633	0.11740	Portfolio12*Urban	0.28092	0.28065
Portfolio2*white	0.53913	0.06374	Portfolio13*Urban	-0.65841	0.05001
Portfolio3*white	0.01879	0.08656	Portfolio14*Urban	-0.51292	0.11779
Portfolio4*white	0.09528	0.07486	Portfolio2*subway	0.43477	0.13254
Portfolio5*white	0.68453	0.09859	Portfolio3*subway	0.23336	0.19460
Portfolio6*white	-0.25596	0.15579	Portfolio4*subway	0.54305	0.16965
Portfolio7*white	-0.17297	0.04568	Portfolio5*subway	0.44399	0.21741
Portfolio8*white	0.28432	0.09361	Portfolio6*subway	0.35442	0.37152
Portfolio9*white	0.08076	0.26010	Portfolio7*subway	0.31879	0.08144
Portfolio10*white	0.18569	0.04133	Portfolio8*subway	0.64761	0.15590
Portfolio11*white	1.08915	0.10609	Portfolio9*subway	1.65684	0.47853
Portfolio12*white	1.34863	0.36191	Portfolio10*subway	0.24739	0.06741
Portfolio13*white	0.11642	0.06923	Portfolio11*subway	0.37265	0.15279
Portfolio14*white	1.15754	0.19855	Portfolio12*subway	0.69147	0.62243
Portfolio2*Urban	0.29309	0.06634	Portfolio13*subway	0.04302	0.12119
Portfolio3*Urban	0.15155	0.09372	Portfolio14*subway	-0.07964	0.32474

VITA

Hyung-Gun Kim was born in Jeju, South Korea on March 13, 1975, the son of HwaSun Jang and YongWook Kim. He completed high school at Jeju-Jeil High school in 1994 and received a Bachelor of Arts degree in Business Economics from California State University at Long Beach in 2001. He then entered the Graduate School in the Department of Economics at the University of Missouri at Columbia in 2002.