

# Consumer valuations of fuel economy - A study of the Finnish automobile market

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### **Consumer valuations of fuel economy - A study of the Finnish automobile market**

The diffusion of energy-efficient technologies can play an integral role in mitigating the detrimental effects of energy use to the environment. However, a host of studies have concluded that the market for conservation technology investments does not operate efficiently and thus does not guarantee an optimal level of investment in energy-efficient technologies. The aim of this study is to discuss whether suboptimal consumer choices contribute to the seemingly slow diffusion of conservation technologies such as automobile fuel economy. Indeed, we aim to find out whether consumers are giving an appropriate amount of weight on future fuel costs when purchasing vehicles - an underweight on operating costs would effectively slow down the diffusion of fuel-efficient vehicles. Furthermore, if consumers do not fully account for the future gasoline costs when purchasing a vehicle, gasoline taxes will fail to secure an optimal level of fleet fuel economy and more paternalistic policies are warranted.

This study consists of a review of the earlier literature on consumer fuel economy choices and discrete choice models of the vehicle market as well as an empirical study of the Finnish vehicle market. In the empirical part of this study we will employ discrete choice methods initially developed by Berry (1994) and Berry et al. (1995) and follow quite closely a nested logit specification presented by Allcott et al. (2011) to disentangle consumer preferences for fuel economy. Our dataset contains new vehicle registrations as well as vehicle characteristics and prices for 2005-2011 in Finland. The existing literature does not offer any clear consensus as to whether consumers are making optimal price-fuel cost trade-offs. Similar to Allcott et al. (2011), our study suggests that consumers are underweighting future gasoline costs compared to the upfront vehicle price.

**KEYWORDS:** automobile market, consumer choice, fuel economy, discrete choice models, price endogeneity, nested logit, energy paradox, conservation technology

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# 1 Introduction

Traditionally the discussion in energy and environmental economics focuses on correcting market failures, such as externalities in the energy market by e.g. Pigouvian taxes. An alternative point of view to the discussion has been the diffusion of conservation technology - green technology development and diffusion can play an integral role in the mitigation of the detrimental effects of energy use on the environment especially in the long run. As Jaffe et al. (1994a) put it, new, efficient technologies can help alleviate the trade-off that seems to exist between economic welfare and the conservation of the environment.

However, a host of studies have concluded that the market for conservation technology investments does not operate efficiently and thus does not guarantee an optimal level of investment in energy-efficient technologies. This problem is sometimes referred to as the 'energy paradox'. This study focuses on one potential reason for the inefficient level of conservation technology investments, namely that consumers might suffer from myopia when purchasing energy-using durables. Conservation technology investments are typically characterized by a trade-off between higher upfront costs and reduced operation future costs. Indeed, the aim of this study is to discuss whether consumers are 'capable' of making optimal cost trade-offs by giving an appropriate weight on the savings in operation costs occurring at some point of time in the future and thus maintaining an optimal degree of investment in conservation technologies. We will apply this question particularly on automobile fuel economy. Our research question indeed is whether consumers undervalue the impact of fuel savings when purchasing vehicles. Our empirical study also aims at giving a measure to the possible undervaluation.

One obvious reason for investigating whether such sub-optimization exists is its implications on the effectiveness of the environmental policy tools related to the automobile market. Indeed, most economists argue that gasoline taxes are the optimal instrument for correcting for the environmental externalities caused by gasoline combustion by vehicles. In addition to directing consumers towards purchasing vehicles with higher fuel economy, taxes also make consumers adjust their behavior in terms of vehicle miles (or kilometers) travelled and thus reduce gasoline use also on that margin. However, if consumers are short-sighted and thus do not fully account for the future gasoline costs when purchasing a vehicle, gasoline taxes will fail to secure an optimal level of fleet fuel economy. In this case fuel economy

standards, such as the CAFE standards on the US, or alternatively vehicle purchase taxes progressive with respect to fuel economy (such as in Finland) would be warranted. Furthermore, gasoline costs account for an important part of the consumption of Finnish households, and thus any sub optimization in the area might result in important welfare losses.

The methods used in this study include a literature review as well as an empirical study of the Finnish automobile market. The aim of the first, theoretical part of the literature review is to shed light on how to incorporate consumer myopia into economic models of consumer choices over time and answer the question of whether sub-optimal consumer choices are a plausible explanation for the so-called ‘energy paradox’. The latter part of our literature review attempts to shed light on the existing literature on consumer choices of automobiles and fuel economy. The literature contains a host of studies either investigating the effect of gasoline price changes on fleet fuel economy, the willingness of consumers to pay for fuel economy or the optimality of fuel economy choices. Our main focus will be on discrete choice models, since they are able to parameterize consumer preferences when it comes to different vehicle characteristics. Some ‘reduced form’, market-level studies will be also discussed however to obtain a more complete picture of the existing research on the subject. The existing literature does not offer clear conclusions as to whether consumers are making optimal price-fuel cost trade-offs. A majority of the studies find that consumers do react to some extent to changes in gasoline prices, but might not fully respond to them in terms of automobile fuel economy choices.

In the empirical part of this study we will employ discrete choice methods initially developed by Berry (1994) and Berry et al. (1995) for the automobile market and later employed by e.g. Allcott et al. (2011) and Sawhill (2008). We follow quite closely a specification presented by the Allcott et al. (2011) paper, but employ a dataset on the Finnish automobile market. Our results indicate, similarly to the latter study, that consumers do not seem to take fully into account the lifetime fuel costs when purchasing a vehicle. The results are also in line with a survey conducted by the Finnish Transport Safety Agency Trafi (2012b) which found that 24% of the respondents do not take fuel consumption into account at all when purchasing a vehicle. However, the ‘reduced form’ methods employed e.g. by Busse et al. (2012) tend to come to the opposite conclusion of consumers being perfectly capable of making optimal cost trade-offs. Furthermore, our model does suffer from some robustness issues due to the small amount of observations in our dataset as well as problems in the

identification of consumer preferences for fuel economy and other vehicle characteristics. More research will be needed to obtain a clearer picture of consumer valuations of fuel economy and to make correct policy recommendations. Nevertheless, our study does contribute to an area of economic research where no clear consensus yet exists and also extends the discussion to the Finnish automobile market.

We will begin with a brief discussion of the models and explanations the economic literature has thus far given for the potentially suboptimal consumer behavior. In Section 3 we will turn to the existing literature on consumer vehicle choices. We will go through in length the methods used and the results obtained thus far by studies on consumer valuations of fuel economy and the optimality of their fuel economy choices. Section 4 will discuss our own discrete choice model of the Finnish vehicle market.

## **2 Behavioral barriers to conservation technology diffusion**

For decades there have been doubts about the efficiency of the market for consumer conservation technology investments, which is characterized by consumers trading off the upfront capital costs to future operating costs (Greene, 2010). This apparent market inefficiency is what Jaffe et al. (1994) refer to as the energy paradox: conservation technologies aren't adopted by consumers as fast as would seem rational and cost-efficient. Howarth et al. (1993) call this the 'efficiency gap' and define it as the differential between the actual level of energy efficiency and the level that could be obtained ideally at prevailing prices were conservation technologies more widely adopted. The authors cite a study by the US National Academy of Sciences, which found that energy use –related carbon emissions could be reduced by 37% if energy-efficient technologies were adopted to the point that would seem optimal under current economic conditions. Another way to express the apparent existence of the energy paradox is through the implicit discount rates that would be consistent with the actual conservation technology investment decisions made by consumers. In a seminal work Hausman (1979) estimated average discount rate consistent with consumer purchases of air conditioners to be 25%. He also found that the discount rate used correlated heavily with the consumer income; according to his findings, the discount rate falls from 39% for households with income under \$10,000 to 8.9% for household with income between \$25,000-\$35,000. Ruderman et al. (1987) on the other hand estimated a discount rate



between 20 and 800% per year. Thus it would seem that consumers are passing up investment opportunities that would yield much more than standard financial instruments. (Howarth et al., 1995)

The choice of technology naturally affects the level of demand for energy – the existence of an energy paradox would make the demand for energy sub-optimally high. Then the environmental and energy policy issues would be two-fold: first, the energy prices should be corrected to reflect the full social cost of energy use due to the externalities of energy use and the fact that the environment is a public good. Second, market and behavioral barriers to technology adoption should be removed to decrease the demand to the socially optimal level. (Howarth et al. 1993). However, at least the theoretical literature is quite inconclusive as to whether such an energy paradox exists and whether it is a result of a market failure and thus requires policy intervention. Several market failure and non-market failure explanations exist for the seemingly slow rates of investment in the literature, of which Thollander et al. (2010) and Jaffe et al. (1994) among others provide a classification. Market failure explanations include e.g. imperfect information, if the market fails to provide enough information for consumers to make sophisticated decisions due to its public good nature, and thus consumers either do not know about the existence of the technology or do not have sufficient knowledge of its attributes to assess its efficiency (Jaffe et al., 1994). Non-market failure explanations on the other hand usually assume some costs faced by the consumer when adopting a certain technology that are not taken into account in simple calculations. For example, the adoption of a new technology can be costly to a consumer because of e.g. having to learn how to use it or who are the reliable suppliers.

Our main area of interest, however, will be to see whether some ‘market barriers’ related to consumer decision-making, or ‘behavioral barriers’, exist to make conservation technology investment decisions suboptimal. Conservation technology investments are typically characterized by trading-off higher upfront costs for reduced operation costs in the future. Indeed, the question is whether consumers are ‘capable’ of making optimal cost trade-offs and thus maintaining an optimal degree of investment in conservation technologies. The discussion in the literature regarding the rationality of consumers when making energy efficiency investments has gone on for decades. Most of the economic literature discussing consumer irrationality and energy efficiency investments do not forgo the concept of utility maximizing behavior altogether, but rather concentrates on finding characteristics of actual

decision-making that can be integrated in formal models of investments in conservation technology. The purpose of this chapter is to look more closely into some of the possible caveats.

## 2.1 Time inconsistency in decision-making

As noted, an important aspect of decision-making over conservation technology investments is how consumers assess upfront capital costs to be paid now versus operating costs to be paid in the future. The question is whether consumers give too much weight to the present at the cost of future. This tendency would naturally undermine investments in conservation technologies, which are characterized by high upfront and lower user costs. As noted above, various studies have found consumers using higher discount rates to assess future vs. present costs than can be justified by the opportunity cost of funds acquired from the market. Indeed, what seem to be irrationally high discount rates used could actually result from individuals emphasizing current savings at the cost of future ones more than would seem rational by economic theory.

O'Donoghue et al. (2001) define time inconsistency as a person's preference for well-being at a certain point in time relative to a later point in time increasing when the earlier point in time gets closer. The relative preference between the two points does not stay constant over time, but changes as time passes. Thus people seek immediate gratification and procrastinate. The model of "hyperbolic discounting" (e.g. Mahajan et al., 2010 and Shui et al. 2005) is an often-used formal characterization of present-biased behavior. Instead of the discount factor  $\delta^{t+s}$  used in time consistent discounting when comparing utility acquired in two separate points in time, in the hyperbolic discounting model all future utilities are discounted with the factor  $\beta\delta^{t+s}$ . This means that when comparing two points of time in the future, only the standard discount factor  $\delta$  matters, but when comparing the present time and any point in the future, an extra weight is given to the present time that cannot be explained by time-consistent discounting. Then a person's intertemporal preferences  $U^t$  can be expressed as:

$$U^t(u_t, u_{t+1}, \dots, u_T) \stackrel{\text{def}}{=} \delta^t u_t + \beta \sum_{\tau=t+1}^T \delta^\tau u_\tau$$

where for  $\beta < 1$  the person has a preference for the present over any future point in time. (O'Donoghue et al., 2001).

As Mahajan (2010) notes, the hyperbolic discounting model can be utilized to explain phenomena such as addiction, as well as under-investment in apparent high-return choices, such as fuel economy. Indeed, giving too much weight to the present when comparing future costs of use against current upfront costs, i.e. not being willing to spend 1 euro more upfront to save exactly 1 discounted future euro, would certainly result in a consumer not investing enough in fuel economy. Shui et al. (2005) study the time consistency of consumer behavior when it comes to the credit card market, and determine an estimation of  $\beta = 0.80$  for the present-bias factor. The authors also identify two types of present-biasedness, namely sophisticated and naïve. The sophisticated type is characterized by the knowledge of own present-biasedness and ability to predict own future behavior. The naïve type simply has irrational expectations of e.g. the future usage of the good, i.e. believes that will have no self-control problems related to behaving as would seem rational at present.

## **2.2 Imperfect expectations and bounded rationality**

As Allcott (2010) puts it, consumer choices depend not only on preferences, but also on beliefs or expectations about the way the final outcome of a decision depends on the choices made. In the context of conservation technologies such as fuel economy, this would mean that consumer's beliefs of future user costs of different automobiles affect their final vehicle choice. Allcott (2010) questions the ability of a consumer to understand how each product attribute affects final utility and states that these "imperfect beliefs" can be caused by imperfect information about product attributes, biased expectations over future usage or bounded computational capacity.

The concept of bounded rationality often comes up in the literature discussing consumer conservation technology investment decisions. Sandstad et al. (1993) note that the problem with economic models that consider consumers as rational decision-makers used to investigate conservation technology investments usually assume that consumers are able to solve highly complex optimization problems to find out the lowest cost or highest return investment options. Simon (1986) would rather describe consumer behavior in terms of 'bounded rationality'; consumers make decisions subject to attention, resource and information processing ability constraints. In addition to bounded computational capacity,

bounded rationality can present itself also in the context of fast technological development, where decision-makers have to rely on partial information when making energy efficiency-related investments. The assumption of bounded rationality then increases the appeal of e.g. appliance standards as a policy tool, since even with accurate labeling consumers would still be unable to make the necessary calculations to make energy efficient investment decisions (Sanstad et al. 1993).

When it comes to consumer valuation of fuel economy, the notion of less than rational decision-making and the difficulty for consumer to evaluate own future behavior has been documented by interview studies. Turrentine et al. (2007) conducted structured interviews of dozens of households only to find out that none of them “analyzed in a systematic way” their vehicle choices or gasoline expenditures. Furthermore, Larrick et al. (2008) realized that speaking of fuel economy in terms of miles per gallon, as is customary in the United States causes a systematic error in consumer’s comparisons of fuel economy between vehicles.

Howarth et al. (1993) on the other hand illustrate the effects of imperfect beliefs about energy efficiency on the level of energy efficiency achieved by the market equilibrium. In their model the imperfections in expectation formation can result in a market outcome where appliances with ‘too high’ energy intensity are produced and purchased. The model assumes that a consumer can choose from a variety of energy-using appliances, each using an amount  $e$  of energy. Then if the price of energy is  $q$  and the price of the appliance is  $p$ , the total cost of buying and using the appliance is  $qe + p$ . However, consumers might not have exact knowledge of the energy efficiency  $e$  of each appliance, in which case they form an expectation  $e^*$  of it based on publicly available information and personal experience. Then consumers choose the device that minimizes ex ante ownership cost  $p + qe^*$ . In addition, a large number of producers are assumed to exist with cost function  $c(e)$ , where  $c'(e) < 0$  and  $c''(e) > 0$ . In the market equilibrium, it must be that  $p = c(e)$ , but since  $e$  is an endogenous variable, we must have some additional equilibrium condition to define it. Indeed, an equilibrium in the case of perfect information must minimize  $qe + p$ , i.e.  $c'(e) = -q$ . The case of imperfect information, however, gives a quite different market equilibrium. If we assume that the expectation  $e^*$  depends on the actual energy intensity  $e$ , i.e.  $e^* = f(e)$ , then the consumer minimizes  $c(e) + qf(e)$ , which gives us  $c'(e) = -qf'(e)$ .

Howarth et al. (1993) illustrate the implications of such a model with an example. If we assume that  $f(e) = (e + 1)/2$ ,  $c(e) = 1/e$  and  $q = 2$ , then the perfect information equilibrium gives us an energy intensity of  $e = (1/2)^{1/2}$ . In the imperfect information case on the other hand the energy intensity equals  $e = 1$ , which is higher than in the perfect information equilibrium, even though  $e^* = f(1) = 1$  as well. The example illustrates that even though the expected energy intensity might actually coincide with the expected intensity in the imperfect information case, the outcome may not be optimal (higher energy intensity compared to the perfect information case) due to the manner of expectation formation of consumers. The point is thus that consumer expectation formation affects the outcome of the market for energy-using appliances even though imperfect information wouldn't be a problem per se, if information is not provided for free in the first place. Naturally, a consumer would be better off (pay lower user costs) with an energy intensity equaling  $e = (1/2)^{1/2}$ , and thus would be willing to pay for the accurate information not provided freely in the market place, so that the manner of expectation formation wouldn't be an issue. But if the cost of the information at the market exceeds the gain in utility, the information goes unpurchased and the market outcome remains suboptimal in energy efficiency terms.

Other caveats to rational decision-making in energy efficiency investments that have been mentioned in the literature are inertia and loss aversion. Inertia refers to the tendency of individuals to keep to established routines and try to reduce uncertainty and change in their living environments. They thus tend to ignore problems, such as energy inefficiency, if it requires from them a change in routines. One result of inertia is the fact that environmental decisions often begin from small changes in behavior that lead to bigger ones. (Thollander et al. 2010). Delucchi (2007) describes loss aversion as the tendency of consumers to rather avoid a loss of a certain amount of money than gain the same amount of money. Thus if the returns of an energy efficiency investment are highly uncertain, this tendency will result in a lower level of investment since consumers will be "conservative" in estimating the costs and benefits of the investment.

Above we discussed some theoretical explanations for the empirically observed paradoxically high implicit discount rates when it comes to conservation technology investment related to consumer behavior. Of course, one could argue that the high implicit discount rates do actually reflect optimal behavior by consumers, meaning that the discount rates that consumers apply to conservation technology investments should indeed be higher

compared to other investments due to higher uncertainty related to the returns of the investment— then no market failure would be taking place. Sutherland (1991), for instance, explain the high implicit discount rates with the Capital Asset Pricing model. However, Howarth et al. (1993) state that it still seems that while the returns on energy efficiency investments are uncertain for consumers, a rational person would not pass up an investment yielding an expected return of 20-800% when alternative investments are expected to yield considerably less.

Thus although higher than expected discount rates for energy efficiency investments seem like a convenient explanation for why seemingly cost efficient investments aren't carried through by consumers, it is doubtful whether it would be rational to apply such high rates to conservation technology investments. Indeed, behind the empirically observed high discount rates there may be behavioral factors at play biasing consumer decision-making over time. In the next section we will turn to discussing the empirical question of which relative weight do consumers actually give to the future gasoline costs of a vehicle purchased at present time. Answering this empirical question would shed light on the question of whether an energy paradox really exists and whether it could be caused by consumers not trading-off 'optimally' the upfront and user costs, as discussed in this section.

### **3 Modeling vehicle choices and fuel economy – A literature review**

After having shed light on the theoretical discussion surrounding the role of consumer behavior in conservation technology diffusion, we turn to discussing one area of implementation of the theory, namely automobile fuel economy. Our main question of interest is whether consumers are optimizing their vehicle choices when it comes to fuel economy, and in this section we will study the literature on consumer choice models of the automobile market with the aim of answering this question. Discrete choice models especially offer a good framework for studying the automobile market and the automobile choices, since they can offer us specific estimates of consumer demand parameters and describe well the automobile market, which is characterized by consumers choosing between highly differentiated products.

Some studies can offer us direct insight on the question of how consumers weigh upfront capital costs (vehicle price) and future discounted operating costs (mainly gasoline costs). In

addition, we will be interested in discussing studies that answer questions such as whether and how consumers respond to changes in gasoline prices, since even though they do not offer direct answers on its optimality, they still shed light on consumer behavior when it comes to choosing vehicles with different fuel economy ratings depending on the lifetime operating costs. For instance, many studies are inspired by the question of how demand for fuel economy changes when gasoline prices change.

In addition to demand models, some reduced-form, aggregate level studies are shortly discussed in comparison to discrete choice models. An example of an alternative approach to estimating the effect of gasoline prices to vehicle fuel economy is simply regressing average fuel economy with respect to gasoline prices and other variables over time (e.g. Li et al., 2009). While these studies allow us to form a more complete picture of the current knowledge of the effect of gas prices on the vehicle market, they do not separate the influence of consumer and producer behavior on the market outcome and thus do not allow us to determine the required consumer preference parameters. Indeed, producer responses to gasoline prices can distort the observed market response to e.g. changes in gasoline prices. McManus (2005), for instance seeks to shed light on the role of consumer direct incentives in why apparently so little change in low fuel economy vehicle market shares has taken place despite the large changes in fuel prices.

The section will serve two purposes. The first one is to draw conclusions from past literature of the way consumers behave when purchasing vehicles as well as how the vehicle market reacts to changes in gasoline prices. Secondly and in addition to a literature review, this section will equally serve as a preparation for our own model introduced in Section 4, as the methods discussed here will be applied in that section. Thus this section serves to justify the choices made later on in our own model. In the following section we will introduce discrete choice models. Introducing the basic characteristics of the discrete choice models enables us to critically study the literature on the subject and to understand the model specification choices in past literature. Then we will move on to discussing the concrete applications to consumer choices of fuel economy.

### **3.1 Introduction to discrete choice models of automobile demand**

Discrete choice models are applied when studying demand and market outcomes in cases where the market to be studied is characterized by differentiated goods instead of a

continuous set of goods (Berry, 1994; Helfand et al., 2009). As Silberhorn et al. (2010) put it, a “utility-based choice on the relative attractiveness of competing alternatives from a set of mutually exclusive alternatives is called a discrete choice situation”. Whereas ‘traditional’ consumer choice analysis, where consumers make their choice from a continuum of alternatives goods, allows one to plausibly assume all the consumers to be using the same behavioral rule, qualitative, or discrete, alternatives require one to assume a distribution behavioral rules being used by consumers (McFadden, 1974). This is exactly what the discrete choice models do by incorporating the random utility hypothesis. The purpose of this chapter is to act as a short introduction to the characteristics of discrete choice models, which then allows us to later discuss their implementation to automobile fuel economy.

### 3.1.1 *Discrete choice and random utility*

As stated in the definition of discrete choice situations given by Silberhorn et al. (2010), utility-maximization is the foundation of all discrete choice models. To be exact, embedded in the model is a behavioral assumption referred to as the *random utility maximization* (RUM) model. The fundamental principle of random utility maximization is the assumption that a stochastic component enters the consumer utility function directly, and not merely to the aggregate demand function. This component is usually interpreted as representing the characteristics of either the good or the consumer affecting utility but unobserved by the econometrist (Brown et al., 1989).

The problem in the initial empirical work on demand modeling was the fact that it was based on the assumption of a market consisting of only one type of consumer or a ‘representative’ agent. When empirical observations didn’t fit these models of a utility-maximizing agent, as was often the case, the model offered few explanations besides problems in data gathering (McFadden, 2001). The attractiveness of random utility discrete choice models when applied to the estimation of consumer choice comes from the fact that while still relying on the assumption of utility-maximizing behavior, they allow for a random component across individuals that is often witnessed in choice data (Brown et al., 1989). They thus not only offer a theory of the structure of *mean behavior*, but also give insight to the distribution of individual behavior around this mean (McFadden, 2001). The point of the random utility specification is thus to take into account the variances across individuals in preferences and choices to allow for less restrictive demand models.



The derivation of the discrete choice setup from the random utility assumption has been described by McFadden (1974) in his seminal work and repeated more recently by Train (2003) and Phaneuf et al. (2009), for instance. The utility is described as:

$$U = V(s, x) + \varepsilon(s, x),$$

where the component  $\varepsilon$  captures the part which the individual knows with certainty and affects his/her choice, but which the econometrist cannot observe.  $V$  on the other hand refers to the ‘representative’, or deterministic part of the utility function. The term  $x$  represents an alternative belonging to a universe of objects of choice  $X$ , and the term  $s$  represents the characteristics of the consumer affecting his/her utility.

Now the random component  $\varepsilon(s, x_j)$  for an alternative  $j = 1, \dots, J$  has some distribution across consumers, and we denote the joint cumulative distribution function of the random component over all the alternatives by  $F(\varepsilon_1, \dots, \varepsilon_J)$ . Thus  $F(\varepsilon_1, \dots, \varepsilon_J)$  defines the joint probability that the stochastic utility components  $\varepsilon$  for each alternative  $x_j$  are below  $\varepsilon$  some value  $\varepsilon_j$ . Now we can use this distributional assumption to derive the probability  $P_i$  of a random consumer choosing an alternative  $x_i$ . A consumer chooses  $x_i$  if it maximizes his/her utility, i.e. if  $V_i + \varepsilon_i$  is greater than  $V_j + \varepsilon_j$  for any  $j = 1, \dots, J$ , given that  $\varepsilon_1, \dots, \varepsilon_J$  are distributed according to  $F$ . We thus want to derive the probability that

$$\varepsilon(s, x_j) \leq \varepsilon(s, x_i) + V_i(s, x) - V_j(s, x) \text{ for all } j = 1, \dots, J$$

Given that the utility maximization condition holds for any given value of  $\varepsilon_i$  (denoted by  $\varepsilon$  below), one obtains

$$P_i = \Pr(U_i > U_j) = \int_{\varepsilon=-\infty}^{\infty} F_i(\varepsilon + V_i - V_1, \dots, \varepsilon + V_i - V_J) d\varepsilon \text{ for all } j = 1, \dots, J$$

where  $F_i$  is the derivative of the joint cumulative distribution function with respect to its  $i$ th argument. See Appendix A for a more specific presentation of the derivation of the choice probabilities from the random utility specification. We thus have an expression for  $P_i$  which depends among other things on the shape of the joint cumulative distribution. (The choice probability multiplied by market size naturally gives us the market share of a given alternative.) Indeed, the next step in finding out the probability of some alternative  $x_i$  being

chosen is defining the joint cumulative distribution function  $F$ . As we will soon find out, significant restrictions have to be placed on the characteristics of the distribution if one wants to be able to solve analytically the probabilities  $P_i$ .

### 3.1.2 *The distribution of the error component*

The most typical distributional assumptions are multinomial logit, nested logit as well as mixed logit or random coefficients. Below we will discuss the advantages and limitations of each of them. Our discussion of multinomial logit will mostly serve to illustrate the problems of too simplistic assumptions on the distribution of the error component, while nested logit and random coefficients are more relevant to empirical work applied to automobile fuel economy.

The foundation of the simple (multinomial) logit model is the Independence of Irrelevant Alternatives assumption (IIA) first introduced by Luce (1959). McFadden (1974) states the assumption in terms of the probabilities  $P$  that a consumer drawn randomly chooses a particular alternative  $(x, y)$  from a set of alternatives  $(B)$  as

$$\frac{P(y|s, \{x, y\})}{P(x|s, \{x, y\})} = \frac{P(y|s, B)}{P(x|s, B)}$$

Thus the IIA assumption stipulates that the probability of  $x$  being chosen relative to  $y$  is the same regardless of whether there are other options in the choice set or not. Indeed, the binary choice between  $x$  and  $y$  is independent of other ‘irrelevant’ alternatives. While the IIA assumption is thus quite restrictive, its advantage is the fact that it allows the econometrist to derive the choice probabilities mentioned in the previous section in the analytical form. See Appendix B for an illustration on how to obtain the choice probabilities of a given alternative given the IIA assumption. Allcott et al. (2010) illustrate the assumption with an example from the automobile market: if the price of one SUV model increases, assuming IIA would mean that the substitution to e.g. a used compact car would be the same regardless of whether a used SUV is also available as an alternative. The example shows that a model that relies on the IIA assumption cannot take into account the fact that some alternatives in the alternative set may be close substitutes to one another (e.g. a new and a used SUV), while others are not (an SUV and a compact car, for instance).

Train (2003) notes that while the IIA assumption is too restrictive for many choice situations, it does have its advantages in others. The stochastic part of the utility function depends on the model specification as it represents the part of a consumer's utility not observed or accounted for by the econometrist. Thus if the choice model is well specified and the stochastic component only contains white noise, the IIA assumption is quite realistic. Train's argument however loses its appeal in many empirical applications, since taking into account all the characteristics of the alternatives affecting consumer utility is usually impossible, especially when it comes to the automobile market where factors affecting vehicle choice are numerous and sometimes complicated to quantify.

The multinomial logit specification is quite rare in applied work especially when it comes to the automobile market due to the restrictiveness of the IIA assumption. Nested logit is often employed in the literature, since it relaxes the IIA assumption but maintains most of the computational simplicity of the simple logit. Indeed, the nested logit choice probabilities can also be given a closed form (as we will illustrate in Section 4). While multinomial logit assumes the error terms to be distributed i.i.d. extreme value type I, which implies that they cannot be correlated between alternatives, the nested logit model allows for correlation between the error terms of alternatives inside predefined groups of alternatives. Indeed, the alternatives are divided into nests consisting of similar alternatives, and the IIA assumption holds between nests but not inside them. (Heiss, 2002). Nested logit thus allows the error terms to have an alternative specific, but unobserved, information content that is relevant to the final choice. For close substitutes, this information content may be similar and thus the error terms can be correlated (Silberhorn et al., 2010). In essence, when using nested logit the econometrist defines the distributional characteristics (and thus substitution patterns) by choosing the nesting structure.

When it comes to nested logit one challenge is thus determining a nesting structure that captures the as closely as possible the true substitution patterns between vehicles. In the automobile market literature, a typical nesting structure divides vehicles into classes such that the lowest level choice then concerns the vehicle (typically mark and model combination). Allcott (2009, 2010), for instance, divide vehicles into two-seaters, sedans and trucks, with size-related subcategories for the first two and intended use-related categories for the last one. Gramlich (2009) employs tree-level nests, each level being a more specific vehicle class. Mohammadian et al. (2003) define six high level classes, whereas the second choice stage

contains four vintage classes. Goldberg (1998) on the other hand uses a quite simplistic nesting structure where the choices at each level from highest to lowest are ‘Buy a car’, ‘Buy a new car’, ‘Vehicle class’ and ‘Domestic or Foreign’. This choice is justified by the author first of all with the fact that it reduces the computational burden of the model, and secondly with the fact that the vehicles belonging to each class on the third level appeared to be very similar in characteristics, and particularly, in fuel economy. Indeed, survey data allows West (2004) and Goldberg (1995, 1998) to set to first level choice to concern the amount of vehicles purchased and the choice of whether or not to purchase a vehicle, respectively. Allcott et al. (2009) test alternative nesting structures, including age, continent where the manufacturer is based as well as whether or not a vehicle can be classified as luxury. They find that in their model, the alternative nesting structures have very little impact on the estimated coefficient for lifetime fuel costs, and thus conclude that while their baseline nesting structure may fail to capture some possible substitution patterns, the uncaptured patterns are not likely to crucially change the estimate of the response to gas prices.

As an alternative to nested logit, the random coefficients method (or mixed logit) is also often used in the literature, since it makes even less restrictive assumptions on the distribution of consumer preferences. It assumes, as the name implies, that the coefficients entering the consumer utility function are not deterministic, but stochastic in nature. It thus allows for random variation in tastes with respect to the characteristics of the alternative as well as in how changes in consumer characteristics affect choices (Helfand et al., 2009). The problem with the random coefficients approach is that it requires computing the integral that maps the utility specification into choice probabilities (and thus market shares) from the previous section via simulation (Berry et al., 1995). The clear advantage of the random coefficients specification however is that the substitution patterns between vehicles become more realistic when the valuation of vehicle characteristics is allowed to vary across consumers. For instance, the random coefficients approach takes into account the fact that a consumer that is currently buying a given vehicle is likely to have greater-than-average preferences for the characteristics of that vehicle, and thus would also substitute to alternatives that have these same characteristics (Berry, 1994).

The main difference between the three approaches is thus how the model captures the differences in preferences across consumers. While the variation in consumer tastes only enters multinomial logit models through the additive error term  $\varepsilon$  and nested logit allows for

random taste shocks only through the dummy variables that indicate membership to a nest predefined by the econometrist, the random coefficients approach allows for random taste shocks over all the measures of product characteristics (Berry, 1994; Allcott et al., 2009). Thus when estimating the role of fuel economy in consumer vehicle choices, one argument that supports the use of random coefficients is the fact that preferences for fuel economy are likely to vary quite a lot inside the population: while some green-minded consumers might give quite a lot of weight on fuel economy, many consumers are likely to give more weight to e.g. safety (and thus size). This is exactly what Sawhill (2008) finds in his random coefficients model. Furthermore, Berry et al. (2004) compare survey data containing second choices of vehicles (an indication of substitution patterns) to estimated models of vehicle demand and find that the random coefficients specification best reproduces the substitution patterns indicated by the real life choice data.

Even though random coefficients better captures the substitution effects between vehicles, the use of nested logit may in some cases be reasonable, as it avoids to some extent the pitfalls of simple logit, but still keeps the estimation of the model reasonably simple. Furthermore, it is possible to give the estimated equation an analytical form for the purposes of instrumental variables estimation, and since the analytical form can be solved without simulation, one avoids the impact of the choice of start values and the solution algorithm in the results which plague random coefficient models. As Knittel et al. (2008) note, the problem is that depending on the choice of start values and the optimization algorithm, the model may converge to a number of local extrema, which then has an impact on the final parameter estimates.

### 3.1.3 *Utility specification*

In addition to the distribution of the error component of utility and thus consumer preferences, the choice probabilities naturally depend on the actual functional specification of utility. Since Berry (1994) is the seminal model that acts as the groundwork for most recent models in the literature, we will begin by briefly introducing his model as the baseline specification. In a later section on modeling assumptions, the modifications to this baseline specification are discussed. Berry (1994) specifies the utility of consumer  $i$  from product  $j$  as

$$u_{ij} = x_j\beta - \alpha p_j + \xi_j + \varepsilon_{ij}$$

where  $x_j$  and  $p_j$  refer to the observed characteristics and price of the good, respectively.  $\xi_j$  on the other hand refers to the unobserved but product specific part of utility whereas  $\epsilon_{ij}$  refers to the consumer specific error component. As Berry (1994) puts it,  $\xi_j$  can be thought of as the mean valuation of the unobserved product characteristics among consumers, whereas  $\epsilon_{ij}$  is the variation across consumers around that mean.  $\alpha$  and  $\beta$  are parameters to be estimated. Due to the existence of an alternative (or vehicle) specific error component, the price becomes endogenous – a problem we will discuss more in detail in the next section.

As stated previously, when it comes to simple logit,  $\epsilon_{ij}$  is assumed to be i.i.d. extreme value type I. In nested logit the econometrist divides the goods into nests so that  $\text{corr}(\epsilon_{ij}, \epsilon_{ik})$  equals zero for goods in separate nests and is nonnegative for those inside the same nest (e.g. Allcott et al., 2010; Goldberg, 1998; West, 2004). If random coefficients is used, as do Berry (1994), Berry et al (1995), Bento et al. (2009) and Sawhill (2008) among others, the parameter  $\beta$  is defined as being consumer specific, such that for characteristic  $r$ :

$$\bar{\beta}_{ik} = \beta_k + \sigma_k \zeta_{ir}$$

In this case the utility specification can be rewritten as

$$u_{ij} = x_j \beta - \alpha p_j + \xi_j + v_{ij},$$

where

$$v_{ij} = \sum_r x_{jr} \sigma_k \zeta_{ir} + \epsilon_{ij}.$$

Remember that in the RUM model the expression for utility contained, as the utility expression stated above, a mean utility component specific to each alternative as well as an individual and alternative specific random component. We can thus use this utility specification, as described in the previous section and given a distributional assumption for the error term, to formulate an expression for the market share of a particular vehicle given its utility. Let's denote the mean utility from the alternative  $j$  as:

$$V_j = x_j \beta - \alpha p_j + \xi_j$$

Now the probability of a random consumer choosing  $j$  is then a function of this mean utility and all other mean utilities (vector  $\mathbf{V}$ ):

$$\zeta_j(\mathbf{V}) = \int_{\varepsilon=-\infty}^{\infty} F_i(\varepsilon + V_i - V_1, \dots, \varepsilon + V_i - V_j) d\varepsilon,$$

This expression for the market shares illustrates a problem of the simple logit assumption as stated by Berry (1994): if only the mean utility levels  $V_j$  differentiate the alternatives, since the  $\varepsilon$ 's are identically distributed for all alternatives and thus the mean utility levels then determine market shares, the assumption implies that two alternatives with equal market shares will have the same substitution patterns (and e.g. cross-price elasticities) with any given third product.

### **3.2 Applying discrete choice models to vehicle choice and fuel economy**

Now that we understand the logic behind discrete choice models of vehicle demand, we are able to look more closely into the applications when it comes to the automobile market and especially consumer choices of vehicle fuel economy. The purpose of this chapter is to introduce the existing literature on the subject in terms of the problems faced when estimating demand in with discrete choice models and the solutions found in the literature, as well as discuss the different modeling assumptions employed. Afterwards, we will go through the main results concerning consumer choices of fuel economy.

#### *3.2.1 The endogeneity of price*

An essential problem when modeling demand especially in markets such as the automobile market is the one of omitted variables. Omitted variables are variables affecting choices and thus demand that are unaccounted for by the econometrist because they may be unobservable or difficult to quantify. Vehicle characteristics such as style, for instance, may have an effect on demand, but are hard to quantify for the purposes of econometrical models. Also, the amount of factors affecting vehicle choice may be so large as to make it impossible to account separately for each one of them. The problem that results from the presence of unobserved product characteristics is the endogeneity of price, meaning that the unobserved characteristics entering the error term and the price of a good are likely to be correlated. In discrete choice models such as the one described above, price endogeneity results from the

inclusion of a vehicle specific error component – the component is likely to include vehicle characteristics that are correlated with the price of the vehicle. Failing to account for this fact in a model can give highly misleading estimation results. (Berry, 1994; Berry et al., 1995 etc.)

This problem is not particular to discrete choice models of demand – actually, it is present also in homogenous goods demand models. The standard solution to this problem is the instrumental variables method. However, the IV method cannot be directly applied to discrete choice models due to the fact that the unobservables enter the market share equation in a nonlinear fashion (see the definition of choice probabilities in the previous section). In his seminal work Berry (1994) solved this problem by inverting the market share equation such that the unobservables would actually be linear in the dependent variable. The specification first defined by Berry has become a standard practice in discrete choice models applied to automobile demand. To illustrate it, let's return to the market share equation defined in the previous section and denote the observed market share of product  $j$  by  $s_j$  and the vector of market shares by  $\mathbf{s}$ . Now for the true values of the market shares  $\mathbf{s}$  and the vector of mean utility levels  $\mathbf{V}$ , it holds exactly that:

$$s_j = \zeta_j(\mathbf{V}) \text{ for all } j = 1, \dots, N$$

Now the error term belonging to  $V$  is clearly nonlinear in  $s_j$ . Berry's (1994) insight is that the above function can be inverted such that the aggregate error term  $\xi_j$  included in product mean utility  $\delta_j$  will enter in a linear fashion in the equation to be estimated:

$$\mathbf{V} = \zeta^{-1}(\mathbf{s})$$

The author establishes the existence of a unique  $\mathbf{V}(\mathbf{s})$  that satisfies  $\mathbf{s} = \zeta(\mathbf{V}(\mathbf{s}))$  under weak regularity conditions. The implication is that the observed market shares  $s_j$  together with a distributional assumption of  $\varepsilon_{ij}$  uniquely determine the mean utility levels for each good. We can thus express the mean utility for good  $j$  as

$$V_j(\mathbf{s}) = x_j\beta - \alpha p_j + \xi_j.$$

The above equation can now be employed as estimation equation. As we can see,  $\xi_j$  now enters in a linear manner the equation to be estimated. The dependent variable  $V_j(\mathbf{s})$  is a transformation of the observed market share. As Berry (1994) notes, this poses no problem for



the use of instrumental variables method as in that sense it is no different from using e.g. a logarithmic transformation of the market shares as the dependent variable. The functional form of  $V_j(\mathbf{s})$  depends through  $\zeta_j(\mathbf{V})$  on the distribution of the consumer specific error term. Thus the computational issues related to solving the exact formulation of the dependent variable depend equally on the choice of distribution of the consumer specific error term. If one assumes an i.d.d. extreme value type I distribution, for instance, the computational burden is quite light. To be able to illustrate in a simple manner Berry's (1994) point, we assumed above that the distribution is known exactly and thus contains no extra parameters to be estimated. This means that we assume that the distribution of consumer characteristics affecting consumer choices is known, but this assumption can be relaxed.

Even though the inversion method described above has become somewhat of a staple for the discrete choice models of the automobile market, the actual instruments used in applied work vary. As Sawhill (2008) states, considering supply side price formation gives rise to two approaches to instrumenting price. Namely, as a vehicle price consist of the marginal cost of production as well as a mark-up, one can use shifters of either component as instruments. Berry et al. (1995) as well as Sawhill (2008) use the latter. They employ the fact that in the case of oligopoly markets, the availability of close substitutes lowers the mark-up and thus reduces prices.

Allcott et al. (2010, 2009) on the other hand use the expected lifetime fuel cost when the vehicle was new as an instrument. They actually rearrange the equation such that the vehicle market share becomes an explanatory variable and price becomes the dependent variable, and thus instrument market share instead of price. The rationale behind using vehicle expected lifetime fuel cost when the vehicle was new acts as an instrument for market shares is the stylized fact that the market shares of vehicles with different fuel economy ratings vary with the prices of gasoline. Thus the expected lifetime fuel costs at the time the vehicle was produced acts as an instrument for market shares. The use of this instrument naturally assumes that a panel data set is used. However, as noted by Allcott et al. (2009), this instrument cannot be used for new vehicles, and thus they employ an instrument similar to the one used by Berry et al. (1995). Klier et al (2008) on the other hand do away with the problem of endogenous prices by assuming a model-year-specific intercept, which includes all characteristics of the vehicle and their coefficients, including vehicle price and its coefficient. The authors employ a data set comprising monthly vehicle sales, which allows them to

capture variation in sales in response to monthly changes in gasoline prices, but where vehicle characteristics remain constant for each model year. An aggregate level error term equally captures the effects of macroeconomic shocks. Using controls for these shocks can thus alleviate the simultaneity bias. For instance, household specific factor such as income are likely to be affected by the same macroeconomic shocks and thus can be used to control for this part of the aggregate component of the error term. (Goldberg, 1995).

As noted previously, price is endogenous only if the error term contains an aggregate level component and is not household specific. Studies using sets of micro-level, consumer specific data, such as Goldberg (1995, 1998) and West (2004) assume away the vehicle-specific, aggregate error component, and thus includes only a vehicle and household-specific error term. It is thus typical for studies using micro-level data to assume away the price endogeneity issue.

Berry et al. (1995) and Sawhill (2008) illustrate the effects of the simultaneity bias by estimating their vehicle choice models with both OLS and the instrumental variables method. Their papers essentially present two similar random coefficient models with the availability of substitutes acting as an instrument to account for the endogeneity of price. They both find that if the model were estimated without the assumption of endogenous prices by simply employing OLS, the price elasticity would be largely underestimated compared to what theory suggests for differentiated products markets. Allcott et al. (2009, 2010) show as well that failing to account for the simultaneity bias can give misleading estimates for the impact of fuel economy on vehicle choices. Namely, they find that if the correlation between market shares and fuel economy was not accounted for, their model would give highly downwards-biased estimates of the coefficient for lifetime fuel costs. Furthermore, when not using the instrumental variables method, Allcott et al. (2010) obtain price elasticities having the wrong sign, which they state to be a typical symptom of the simultaneity bias.

### *3.2.2 The endogeneity of fuel economy*

Another endogeneity issue plagues the discrete choice models of the automobile market trying to assess consumer valuation of fuel economy. This is the fact that due to the nature of the car design and manufacturing process, the fuel economy is likely to be correlated with some unobservable vehicle characteristics. For example, the fuel economy rating of a particular vehicle is very closely related to the size of the engine of the vehicle. Some of these

characteristics can be separately accounted for which eliminates the endogeneity issue, whereas some of them are hard to quantify and thus remain in the error term. More generally, product characteristics as well as price are choice variables for the producers, and are chosen given some observed and some unobserved qualities (Gramlich, 2009). For example, the brand value of a hybrid vehicle such as a Toyota Prius for green-minded consumers is correlated with the fuel economy rating of that vehicle, but the brand value is hard to quantify for the purposes of a discrete choice model.

In seminal work on discrete choice models of the automobile market the orthogonality assumption (observed and unobserved vehicle characteristics uncorrelated) was quite common. Berry (1994) and Berry et al (1995), for instance, admit that their assumption of uncorrelated observed and unobserved product characteristics is quite strong and should be relaxed in future work. Gramlich (2009) argues that the parameter estimates obtained in studies not accounting for the endogeneity of fuel economy are biased downwards and thus falsely imply that consumers do not care about fuel economy. A typical approach to eliminating the endogeneity issue is to employ fixed effects if access to panel data is available, since controlling for all the possible vehicle characteristics correlated with fuel economy in a cross-section data set is challenging. Allcott et al. (2009, 2010), for instance, exploit model-by-age fixed effects. They specify the model-specific error term from Berry (1994) as specific for model  $j$ , age  $a$  as well as point in time  $t$  such that  $\xi_{jat} = \xi_{ja} + \varphi_{jat}$ , where  $\xi_{ja}$  captures the model-age fixed effects. As mentioned in the previous section, Klier et al. (2008) use a similar method, but instead of model-age fixed effects they employ model-year fixed effects.

Gramlich (2009) employs a quite original method for controlling for the unobserved characteristics that could potentially be correlated with fuel economy. The author uses the natural logarithm of fuel economy  $\ln(mpg)$  as a proxy to all variables affecting utility that might possibly be correlated with fuel economy. He employs the fact that fuel economy (*dollars per mile = gas price / mpg*) is likely to be negatively correlated with other vehicle characteristics contributing to vehicle utility. The negative correlation, according to the author, results from the fact that car manufacturers face a technology frontier that represents the trade-off between fuel economy and other quality. Manufacturers are then forced to place themselves in some point of the technology frontier, and thus the choice of fuel economy and other quality boils down to the simple choice of mpg. He specifies that this regularity between fuel economy and other characteristics takes place inside a vehicle sub

segment. This method saves the econometrist the effort of trying to control for all the possible characteristics of a vehicle that might be correlated with fuel economy, since due to the technology frontier assumption, all the observed and unobserved characteristics are included in the  $\ln(mpg)$  explanatory variable. Thus the only vehicle characteristics explaining demand are price, dollars per mile,  $\ln(mpg)$  inside a particular vehicle sub segment. One might however question the rationale of the use of  $\ln(mpg)$  by the author to control for unobserved quality, since one could argue that not all unobserved quality is negatively correlated with fuel economy. Furthermore, the terms of the trade-off between fuel economy and other characteristics are likely to become better over time due to the advances in technology.

Bento et al. (2010) and Bento et al. (2009) state that in addition to better modeling substitution patterns between vehicles, the random coefficients approach attenuates the problem of endogenous fuel economy. Indeed, the authors claim that if all consumers are assumed to have similar preferences for fuel economy and they actually do not, this portion of utility will be left in the error term. This would in turn make the error term correlated with fuel economy. Thus using the random coefficients approach, which allows for different fuel economy preferences between consumers, would help reduce the correlation between fuel economy and the error term.

### *3.2.3 Modeling assumptions*

Previously discussed some of the most important pitfalls in estimating discrete choice models of the automobile market, namely the substitution patterns between vehicles, consumer heterogeneity and the endogeneity of price and fuel economy. In this section we will turn to discussing the modeling assumptions made in these studies and their usefulness. Some of them are specifically related to fuel economy while some are more general in nature.

Some models incorporate the fact that vehicle miles travelled might also be adjusted when e.g. gasoline prices change. The models jointly estimate the continuous choice of vehicle-miles-traveled and the discrete choice of vehicle. As noted by West (2002), the choices are highly interrelated, as same factors are likely to lie behind both choices. Furthermore, a gasoline tax, for instance, should impact consumer behavior on both margins, since consumers would start reconsidering their miles driven if gasoline prices rise substantially. Indeed, taking into account the changes in miles driven usually concerns papers in which the authors aim at clear conclusions on policy effects (e.g. Goldberg, 1998; West, 2002; Bento et

al., 2009). The typical framework to be used to model the choices of durable goods and demand for energy in the one introduced by Dubin and McFadden (1984) (e.g. West, 2002). West (2002) and Goldberg (1998) employ a two-step method for jointly estimating the discrete choice of vehicle and continuous choice of vehicle miles travelled which takes into account the fact that the two choices are correlated. Bento et al. (2009) on the other hand assume that, in addition to vehicle characteristics, vehicle miles travelled affects the utility from the vehicle. In their utility specification, user cost enters as price per mile times miles driven, where the miles driven variable is optimized as well.

The models that only include a demand size discrete choice model are referred to as partial equilibrium models (e.g. West, 2004). As stated by West (2004), a partial equilibrium model assumes producer behavior to be constant such that they don't alter their behavior e.g. in response to gasoline price changes. Often the assumptions on supply side are quite similar from study to study, the typical approach being an oligopoly differentiated products model where producers compete by setting prices. The producers are assumed to set prices to maximize profits given the prices set by other producers as well as the current policy, e.g. fuel economy constraints. (e.g. Bento et al., 2009; Goldberg, 1995 and 1998; Berry 1995). More sophisticated models of supply side behavior can often be found in studies with a special focus on the effects of policies on general welfare and supply side profits, e.g. Austin et al. 2004. However, these studies tend to employ simplified demand side assumptions and often assume away the potential problem of consumers underweighting future fuel costs.

As Berry (1994) notes, an outside good has to be incorporated in a model since otherwise the consumers would be forced to choose one good regardless of the overall level of prices and thus only the relative prices would matter (for the good chosen). The outside good basically captures the option of not choosing any of the vehicles included in the model. When using the inversion method by Berry (1994) described above, the outside good enters the equation to be estimated as the log of the market share of the outside good, as the author illustrates for the cases of simple and nested logit. One can of course attempt to estimate the size of the outside good from data, but a more common method used by e.g. Allcott et al. (2009, 2010) and Klier et al. (2008) is to add time dummies to the estimated equation, in which case one can dispose of the term altogether. What the outside good actually represents depends quite a lot on the model specification, e.g. whether new and old car markets are both included. In the models that only include the new car market, the outside good often

comprises all used vehicles in addition to the option of e.g. using public transport. Goldberg (1995, 1998) takes into account the existence of the outside good (the option of not purchasing a vehicle at all) by incorporating as the first level of the nesting structure the choice of whether to purchase a vehicle. This allows the author to reach conclusions such that the vehicle characteristics included in her model do not affect the buy or not buy decision, but only the composition of the fleet of new vehicles.

As stated above, some models, such as e.g. Klier et al. (2008) and Berry et al. (1995), include only the new vehicles market. One can argue that such an approach incorrectly models the substitution and scrappage effects taking place at the vehicle market as a result of changes in gasoline prices and policies. Taking into account the new vehicle, used vehicle and scrap markets is particularly important in studies discussing the effects of changes in gasoline prices to the vehicle fleet fuel economy. Otherwise one wouldn't be able to capture the dynamic effects at play affecting the average fuel economy of new and used vehicles in the economy. Busse et al. (2010) do argue that when studying the effects of gasoline prices on the vehicle fleet, concentrating on new car sales is more justified, since the additions from the newly purchased vehicles to the vehicle fleet are the ones that make an environmental impact, not the used vehicle that simply switch owner. While this is true, one must remember that the scrappage of used vehicles has at least as substantial an environmental impact, since used vehicles are more likely to be gas-guzzlers. Thus being able to model how fast new, fuel efficient vehicles are replacing old ones in the vehicle fleet is important for drawing conclusions on the effects of gasoline prices on the vehicle fleet.

Bento et al. (2009), for instance, model the used car market with a dynamic model where the total stock of used vehicles is that of the previous period bar those that are scrapped plus the new vehicles of the previous period. Furthermore, in their model a consumer decides to scrap a vehicle when its scrap value is greater than the resale value. Goldberg (1998, 1995) on the other hand model the dynamic nature of vehicle choices by, first of all, using a survey data set that includes information on past vehicle purchases and secondly, employing a nesting structure where the highest stage choice is whether or not to purchase a vehicle. However, as noted by Goldberg (1995), this specification still does not perfectly model the dynamic nature of vehicle choices: a consumer might e.g. sell a relatively new car if he could acquire a good enough price or choose to repair an old one rather than to buy a new one. The author states that a more realistic model of the dynamics of vehicle purchases would require a

comprehensive micro-level data set that would include several periods. Indeed, most models in the literature consider vehicle purchase in one period and then assume that the vehicle will be held for the rest of its useful price. Allcott et al. (2010) note that when it comes to taking into account the lifetime fuel costs this assumption is valid in the sense that if a consumer chose to resell a vehicle at any point in time, the future vehicle costs affecting the resale price will simply be the fuel costs over the remaining life. Allcott et al. (2009, 2010) mention another market mechanism that might seemingly attenuate the consumer response to higher gasoline prices, namely higher rates of low fuel economy vehicle scrappage when gasoline prices are high. Allcott et al. (2009) speculate that this supply shift then increases the prices of low fuel economy vehicles.

Vehicle scrappage and substitution between new and used vehicles are not the only dynamic aspects of the vehicle market. Despite the use of panel data, the models of vehicle choice that can be found in the literature usually abstract quite a lot from the true dynamics of the market. For instance, consumer preferences are often assumed to be constant (e.g. Allcott et al., 2009 and 2010), meaning that e.g. the weight given to future fuel costs and the fuel economy have stayed constant across time even though there has been significant variation in gas prices. Furthermore, environmental awareness probably has increased during the last decade, and it is reasonable to assume that this would also have had an impact on preferences over vehicle fuel economy. Train et al. (2007) on the other hand consider the dynamic effects of brand loyalty on vehicle choice.

Moreover, while many models incorporate some assumptions of supply side behavior in their models, typically producer behavior is modeled in a quite simplified manner, and may not capture the true supply side dynamics. In the longer run, car manufacturers are able to adjust the characteristics of their fleet as well as develop more fuel-efficient technologies. Gramlich (2009) does incorporate a model of product characteristic determination by employing the method of moments, with moments defined such that the amount of ex-post regret by producers on the product characteristics chosen cannot be known in advance, and thus choices of characteristics are optimal given the information available at that point in time. (Characteristics are chosen in advance for a future period and cannot be changed later.) Thus the author is able to allow the endogenous characteristics to be correlated with the error term of the model by assuming that the error terms are cost and price shocks that are known to the producer at the time when the characteristics are chosen. On the other hand McManus (2005)

calibrates a nested logit model using price elasticities from previous studies and then simulates the model on counterfactuals to disentangle the effects of gasoline prices and consumer direct incentives on demand for vehicle with different fuel economies. He finds that the seemingly high demand for low fuel economy vehicle in the US despite the rise of gasoline prices in the early 2000's was due to the fact that at the same time direct incentives related to low fuel economy vehicles increased considerably. However, their study does not take into account the fact that consumers might be suffering from myopia.

#### *3.2.4 Data*

The availability of data has been a major concern when it comes to modeling the automobile markets as well as the choice of fuel economy. As more detailed data sets have become available, more precise and sophisticated models have been used. The two types of data typically used in the papers of interest are aggregate level market share data (e.g. registration data) or aggregate level sales data and survey data. Each type of data has its advantages and shortcomings.

Survey data is used by Goldberg (1995, 1998), Mohammadian et al. (2003) and West (2002), for instance. The main reason to use micro-level (usually survey) data when modeling the automobile market is the fact that it allows the econometrist to model more realistically the substitution patterns between vehicles that are subject to consumer heterogeneity. Indeed, when it comes to models using micro level data, data on vehicle characteristics can be interacted with household specific data. As Goldberg (1995) notes, even when using as restrictive a utility formulation as the multinomial logit, the substitution patterns in a model using micro-level data can be quite realistic. This results from the fact that the substitution patterns are not determined only by the functional form of utility, but also by the distribution of household characteristics in the data set. One practical implication is that the econometrist can use a more simple nesting structure. If aggregate levels data is used however, the econometrist has to employ more complicated nesting structures or a random coefficients model to realistically model substitution patterns between vehicles. Berry et al. (1995) and Sawhill (2008) among other use aggregate level data, and thus employ the random coefficients approach. Sawhill (2008) does note still that the assumption made in his random coefficients model of the distribution of taste parameters across consumers might be



unrealistic, and thus micro-level data on consumer characteristics could be utilized to enhance the aggregate-level data in his study.

West (2004) notes one practical limitation of the use of survey data: it does not usually include very detailed data on vehicle characteristics affecting vehicle choice, and thus it would have to be combined with data from other sources to get a more realistic representation of vehicle choice. Another clear downside of survey data is that it is rarely publicly available. Furthermore, survey data rarely extends over long periods of time. When it comes to data length, one can observe a general trend that the more aggregate level data, the longer the span of the data used. E.g. Berry et al. (1995) and Sawhill (2008) use data expanding to the 1970's. Papers using combined or transaction data, such as Allcott et al. (2010), may employ data sets expanding only over less than ten years. As the purpose is usually to make longer run predictions of the workings of the automobile market in terms of fuel economy, one could argue that aggregate data expanding over a longer time period would be preferable to survey data. However, in micro-level data the lack of long time trends are partly made up for by the fact that it often contains data on the past purchases or planned future purchases of vehicles that allow for the modeling of dynamic effects, even though the data in itself was cross-sectional. As mentioned above, another aspect of studies using micro-level data in their specification is the error term, namely that the error component is assumed to be specific to a household and not to the vehicle. (e.g. Goldberg, 1995 and 1998; West, 2002).

Both cross-sectional and panel data have been used in the literature. The most important reason for opting for panel data, as in most econometric applications, is the fact that it allows one to model fixed effects and thus reduces the burden of correct model specification, which is often a major issue in applications to the automobile market (e.g. Klier et al., 2008; Allcott, 2010). As Allcott et al. (2010) note, using cross section data requires an extremely accurate model specification - all relevant vehicle characteristics have to be well parameterized in order for the fuel economy to be uncorrelated with the error term. Indeed, in the literature cross-section data is mostly used in studies that have access to survey data, since including consumer-specific data to enhance the choice model eases the burden of having to model all relevant vehicle characteristics affecting vehicle choice. However, this tradeoff is not only caused by the advantages of micro-level data, but also the fact that long time series of survey data are quite difficult to come by.

A few alternative ways have been used in the literature to account for vehicle prices. Mohammadian et al. (2003) use average prices instead of transaction prices from survey data, and justify this choice with the fact that when it comes to survey data the reported sales prices would be subject to reporting errors and self-selection bias. On the other hand, the use of list price poses similar problems with measurement errors, since most transactions actually take place with negotiated prices. Thus data on actual transactions would seem optimal, but large enough data sets are hard to come by. Allcott et al. (2010), for instance, use an extensive data set of millions of transactions on used and new vehicles from an auction house and a centrally managed network of dealerships, respectively, of which they calculate monthly average prices. On the downside, prices from transaction data do suffer from selection bias, meaning that they usually do not contain all possible vehicle transactions, but merely a sample of the transactions taking place each year. Busse et al. (2010) note that this selection bias can be attenuated by controlling for the characteristics of the transaction, such as geographical location.

### **3.3 Conclusions from the literature and policy implications**

In this section we will discuss the results obtained by the literature in two separate sections. First of all, we look into whether consumers take into account or are sensitive to fuel costs when purchasing vehicles. Time series variation on gasoline prices plays an important role in determining consumer valuations for fuel economy. Indeed, studies attempting to discover the effects of changes in gasoline prices to the fuel economy of vehicles purchased will offer insight on consumer take on fuel economy, since the results allow us to draw conclusions on consumer tendencies in responding to changes in the fuel costs of a vehicle. In these results the consumer behavior relating to assessing upfront costs and costs of use is implied. We will look into the results obtained by both discrete choice demand models as well as reduced form models on the subject. Secondly, we will be interested in studies that can offer direct insight on the optimality of consumer choices of fuel economy.

#### *3.3.1 Do consumers value fuel economy?*

The purpose of this section is to discuss consumer sensitivity to vehicle fuel costs and automobile fuel economy. Most of the studies covered in this section attempt to estimate fuel economy related consumer preference parameters without actually explicitly measuring the trade-off between capital and operating costs when purchasing vehicles. Estimates of the

elasticity of vehicle demand to the user costs of a vehicle can then be drawn from these coefficient estimates. Some studies interpret the results in terms of the effects of gasoline price changes to demand for fuel economy. The preference parameters are estimated for variables such as miles per gallon, dollars per mile or price per mile driven. As Helfand et al. (2009) notes, these models assume that consumers respond in a similar manner to an increase in fuel economy and a decrease in gasoline prices and thus are indifferent to the source of the savings.

Berry et al. (1995), for instance, include fuel economy as miles per dollar in a random coefficients model of vehicle choice as a vehicle characteristic, and they find a statistically insignificant mean coefficient for miles per dollar. However, they find that the standard deviation of the coefficient (i.e. marginal utility) is substantial and significant. In fact, the authors find that the elasticity of demand with respect to miles per dollar declines with the vehicle's miles per dollar rating. They interpret the result such that consumers who buy high MP\$ vehicles are sensitive to changes in MP\$, whereas the MP\$ rating does not affect the purchasing decisions of those purchasing low MP\$ vehicles. Goldberg (1998) estimates a nested logit model with an integrated vehicle utilization model using survey data. The author includes price per vehicle mile as an explanatory variable and obtains an average fuel cost elasticity of -0.5, which implies that consumers do respond to changes in the user costs of a vehicle. However, their simulations indicate that large changes in gasoline prices would be required to induce substantial changes in the average fuel economy.

Gramlich (2009) on the other hand argues that the parameter estimates for fuel economy from studies such as Berry et al. (1995) are biased downwards, since these studies do not take into account the correlation between fuel economy and unobserved quality. The author himself estimates a nested logit demand model with endogenous characteristics and finds that consumers 'care strongly' about fuel economy – he finds coefficients for dollars per mile in all vehicle segments that are negative and significant. Furthermore, he calculates the willingness to pay for fuel economy from the coefficient of dollars per mile, and finds that within a vehicle segment, higher gas prices always mean higher willingness to pay for fuel economy. However, his findings indicate also that when gas prices are low, willingness to pay for higher fuel economy can be negative, which the author explains with the assumed trade-off between fuel economy and other quality. Furthermore, as Gramlich (2009) estimates coefficients for dollars per mile by vehicle sub-segment, he finds that the most fuel economy

sensitive consumers are those buying utility vehicles. The result might seem quite counterintuitive, since one might assume that those buying vehicles belonging to such an overall fuel inefficient sub-segment would not be sensitive to fuel economy. However, the author interprets the results such that they are sensitive to fuel efficiency *given* the choice of sub-segment. In any case, these results contradict those obtained by Berry et al. (1995), who found that those buying fuel-efficient vehicles are the most sensitive to variation in fuel economy.

Bento et al. (2009) estimate a vehicle choice model with an embedded choice of miles driven with survey data, but employ the random coefficients method. They obtain a measure for the elasticity of gasoline use with respect to the price of gasoline, where the responses of vehicle miles travelled as well as vehicle (and thus fuel economy) choice are both taken into account. Their estimate of the overall elasticity is -0.35. The elasticity is only slightly reduced when vehicle choice is assumed to be given. Indeed, Bento et al. (2009) find that the effect of shifting from low fuel economy vehicles to high fuel economy vehicles to the equilibrium gasoline consumption when gasoline prices rise is quite small, and that adjustments in vehicle miles driven account for a more important part of the overall change. However, their model takes into account new and used vehicle ownership and vehicle scrappage, and their simulations imply that over time the increased gasoline prices induce a greater fuel economy of new vehicles relative to used vehicles, which in turn results in increased new car ownership. The advantage of their model is the fact that they include the dynamics effects of substitution to used vehicles and scrappage that are likely to have an effect on fleet fuel economy. However, due to the high computational burden they have to study vehicles only at age, class and manufacturer level.

Klier et al. (2008) estimate a model with monthly data and vehicle fixed effects inside a model-year, to find out the effects of gasoline prices on the demand for fuel-efficient vehicles. They find that the changes in gasoline prices do significantly affect the new vehicles market especially in terms of reducing the share of vehicles manufactured in the US. However, their estimate of the elasticity of average new vehicle fuel efficiency is 0.12, which, in line with the results obtained by Bento et al. (2009), indicates a quite small effect in size. Interestingly, Klier et al. (2008) also find that the response to gasoline prices is greater when the price of gasoline is high. The authors criticize earlier studies for the fact that they do not take into account the possible correlation between unobserved vehicle and consumer characteristics and

*gasoline* prices, although they admit that the economic theory does not give clear indication as to which way this would bias the coefficient estimates. Their study controls for the possible correlation by employing a dataset of monthly sales data and assuming that while gasoline prices vary month-to-month, vehicle characteristic and consumer preferences do not change as often.

The above-mentioned studies are all consumer level (discrete choice) demand models of the automobile markets. Some reduced form studies offer insight on the same question, although they do not tell us demand parameters but instead market reactions. Li et al. (2009) estimate the effects of gasoline prices on fleet fuel economy by regressing the market share of vehicles in a certain mpg group with respect to dollars per mile and some controls. Based on simulations, the authors find that a 10 percent increase in gasoline prices increases the fleet fuel economy by 0.22 percent in the short-run and 2.04 percent in the long-run, both of which indicate a quite modest impact. Li et al. (2009) criticize consumer level studies existing in the literature of the fact that they rarely succeed in modeling realistically the dynamics of new and used vehicle holdings – the claim that even Bento et al. (2009), which is probably the most prominent demand model in this particular area, has to make quite simplifying assumptions on e.g. vintage choices. Furthermore, unlike demand models, they do not attempt to estimate consumer preference parameters and thus claim to avoid the simplifying assumptions required to estimate them. At the same time, this is exactly the problem with their approach – their model cannot say anything about the actual consumer choices, since the market responses they study may be affected by producer behavior as well. Indeed, this might be the reason why their estimates indicate a modest adjustment in fuel economy to gasoline prices – they results may be hiding some adjustment in the adverse direction by producers. Furthermore, they are forced to estimate separate models for new vehicle purchase and used vehicle scrappage decisions. All in all, their model, like other reduced form models, is more susceptible to the ‘Lucas critique’ when attempting form policy recommendations (Lucas, 1976).

Li et al. (2012) regress a similar model and obtain estimates for the elasticity of average fuel economy with respect to changes in gasoline prices. Their model separately takes into account the changes in gasoline prices induced by taxes and non-tax changes in gasoline prices. The authors find that while a one-dollar increase in tax-exclusive gasoline prices increases average fuel economy (in miles per gallon) by 3.6%, the same increase induced by

gasoline taxes would increase average fuel economy by 47.7%. The rationale behind these results is the fact that tax changes may be viewed by consumers as more permanent, and thus the results indicate a much greater sensitivity to gasoline prices than those of Li et al. (2009). Busse et al. (2010) estimate the effect of gasoline prices on new vehicle sales with a series of linear probability models. They find that higher gasoline prices indeed are connected with the purchases of higher fuel vehicles in the new vehicle market; according to their estimate, a one dollar increase in gas prices results in a 20.5% increase in the market share of the most fuel efficient quartile of vehicles. However, the authors remind that since they employ year fixed effects, the results concern within year variation in gas prices and sales. No trend effects can thus be deduced from the data.

As stated above, accounting for the fact that gas price changes may give incentives for manufacturers to alter the relative prices of vehicles with differing fuel economy levels affects the results of such studies. As Langer et al. (2009) state, the fact that manufacturers might assume consumers to rationally take into account relative changes in vehicle fuel costs and thus adjust their vehicle prices accordingly would actually attenuate the effect of higher fuel prices on the market shares. Thus it might seem that the market does not fully adjust to changes in gasoline prices, whereas in fact the loss in attractiveness of low fuel economy vehicles is made up by lower prices from manufacturers. By regressing the manufacturer prices of gasoline on own fuel costs and competitor fuel costs among others, they find that that the coefficient of own fuel costs is consistent with strong and significant consumer response to price of gasoline. The result indicates then that manufacturers adjust the prices they set as though consumers would rationally adjust their demand to gasoline prices. Furthermore, the authors speculate that in the long run the market shares adjust as the profit implications of this manufacturer behavior makes the manufacturers shift production to higher fuel economy vehicles.

### *3.3.2 Do consumers underweight operating costs?*

In the previous section we discussed over consumer sensitivity to fuel economy. While the results offered insight on whether consumers take into account user costs when purchasing vehicles, it did not offer direct answer on the optimality of the cost trade-off, which will be the main interest in this section. The most straightforward approach to estimate the cost trade-off is to add lifetime discounted vehicle fuel costs as an explanatory variable to a demand

model. Constructing an explicit measure of the vehicle lifetime fuel costs allows the econometrist to directly employ the coefficient of this explanatory variable as a measure of consumer myopia.

Allcott et al. (2009) construct a nested logit model to decipher the effect of changing gasoline cost expectations on the market shares and prices of vehicles. They rationalize that in their model where vehicle price is the dependent variable, the coefficient of discounted lifetime fuel costs should be equal to one – a one dollar increase in the discounted operating costs should result into a one dollar decrease in the price of a vehicle. The logic is similar to that used by e.g. Sawhill (2008). They find that a one-dollar increase in the discounted lifetime fuel costs results into only a 0.25 dollar increase in price, suggesting that consumers indeed are ‘myopic’. Allcott et al. (2010) estimate a similar model, and equally find that consumers are myopic, even though the coefficient estimate they obtained for the lifetime fuel costs of a vehicle is considerably higher, indicating that consumers would trade one saved dollar in operating costs to 0.61 dollars in upfront costs.

Sawhill (2008) estimates a random coefficients model similar to that of Berry et al. (1995) and includes the assumption of forward-looking consumers when it comes to driving patterns and gasoline purchasing. The author finds no systematic undervaluation of the operating costs on the average. However, similar to Berry et al., his results indicate quite high variation in the coefficients of operating costs inside the population, which shows that a significant part of the population is actually making inefficient trade-offs even though on average there is no myopia to be detected. Indeed, he finds that 37% of the population weight prices more heavily than operating costs. The author also estimates a simplified model which doesn’t take into account consumer heterogeneity (multinomial logit instead of random coefficients) and measures operating costs with the current cost of driving the car for 100 miles. The results from the estimation of the simplified model indicate that consumers clearly underweight operating costs relative to the upfront capital cost when purchasing vehicles. The increase in elasticity with respect to operating cost in Sawhill’s (2008) complete model compared to that in the simplified model could explain the differences in the results obtained by Allcott et al. (2009, 2010) and Sawhill. Especially, Allcott et al. (2009, 2010) use nested logit, which does not take consumer heterogeneity into account as efficiently as random coefficients. On the other hand, Sawhill (2008) doesn’t find his operating cost elasticities to be particularly

sensitive to the fact that consumers have the option of alternating their driving patterns with respect to changes in gasoline prices.

The problem with the approach adopted by Allcott (2009, 2010) and Sawhill (2008) is that the results may be dependent on the specification of the lifetime fuel cost estimate. While a measure of the fuel economy of a vehicle is usually readily available in a dataset, vehicle miles driven per year, the discount rate used and expected future gasoline costs are more complicated to measure. The assumptions made on these variables then affect the parameters estimate and thus conclusions drawn. Allcott et al. (2010) do test the sensitivity of their parameter estimate to the assumptions made, and no significant changes are observed in the parameter estimates. Furthermore, they claim to employ conservative assumptions such that the bias should rather be away from finding consumer myopia. Sawhill (2008) equally finds that his results are not sensitive to vehicle lifetime mileage and discount rate estimates.

Busse et al. (2010, 2012) adopt quite a different approach to estimating the interactions between gasoline prices and vehicle prices. They estimate a reduced form model that captures the total effect of gasoline prices on vehicle prices while controlling for some vehicle and buyer characteristics. However, from such a parameter estimate one cannot directly disentangle the effect of consumer cost trade-offs and producer responses, for instance. With assumptions for the elasticity of demand for vehicles from previous literature, they estimate whether the recorded price changes comply with rational cost trade-offs. They find no signs of consumer myopia for either the used or new car market.

Li et al. (2012) present similar critique. They note that there is a fundamental identification problem in environmental economics, namely that to assess consumer behavior when it comes to trading off capital and operating costs requires assumptions on consumer expectations of future fuel costs. These assumptions then affect the conclusions on either implicit discount rates or the optimality of the trade-off, depending on the paper in question. They address this question, as mentioned in the previous paragraph, by separating the effects of gasoline tax changes (which are likely to be viewed as more permanent by consumers) and non-tax price changes. However, the authors do not draw direct conclusions on the optimality of consumer responses to gasoline price changes nor do they calculate any implicit discount rates.



### *3.3.3 Conclusions from the literature*

The unfortunate result of the above discussion is that clear conclusions of consumer preferences on fuel economy are difficult to draw. One can safely say that no compelling evidence of consumers totally disregarding future operating costs of their vehicles can be found in the literature. A majority of studies do draw the conclusion that consumers care to some extent about fuel economy. However, some stickiness in market responses to e.g. gasoline prices in terms of average fuel economy does exist, based on the literature discussed above. Indeed, many studies find that the adjustment in vehicle purchasing patterns when gasoline prices rise is quite modest, which would indicate that operating costs are not taken into account in full when purchasing vehicles. Unfortunately, many studies do not tell us whether the valuations are optimal. Studies such as Allcott et al. (2009, 2010) on the other hand do give a direct measure of consumer myopia, but are unfortunately subject to some quite heavy assumptions. Thus while we can safely say that consumers, or at least some share of them, do care for fuel economy, the question of whether their behavior (on average) is optimal remains, alas, an open question. More studies would be needed to address this particular question.

Overall, the difficulty in drawing clear conclusions from the literature arises from the fact that a particular paper usually concentrates on one or a couple of aspects of the problem. In reality, changes in gasoline prices can be expected to cause changes in demand behavior, driving behavior and manufacturer behavior (such as pricing and design), for instance. Thus often the results found by a paper that studies one aspect of the market effects fails to capture others, which then partly undermines the results obtained.

While the literature has succeeded in developing quite tractable models for estimating consumer preference parameters and thus valuations of fuel economy, some development areas remain. First of all, a bulk of the studies in the literature model demand with nested logit. The clear limitation is that in a market such as the automobile one is that it offers a quite simplified presentation of the existing substitution patterns which are dependent on the econometrist's choices. Thus, while various nesting structures have been attempted and found relatively useful, nested logit is still quite rigid in modeling the variety of potential consumer responses to fuel economy. As the automobile market is one where tastes and needs can vary quite a lot, there is a need to allow for more variation in studies. Indeed, the random

coefficient models in the literature seem to point to the substantial variation in tastes for fuel economy. Bento et al. (2009) do make a good attempt to employ the random coefficients approach in a dynamic framework. Of course, with more sophisticated modeling assumptions the computational burden increases.

Another potential improvement to the current literature is a more extensive use of micro-level data, possibly in combination with aggregate level data. The methods were developed already by Berry et al. (1995), and have been implemented by Bento et al. (2009). Replacing nested logit with a random coefficients model with micro-levels data used to enhance the distributions of tastes in the population. While many random coefficient models, such as Sawhill (2008), assume a normal distribution of tastes inside the population, enhancing a study with micro level data would allow for more truthful distributions of consumer characteristics and thus preferences. Consumer preferences could be discontinuous, for instance such that some consumers do not place at all weight on fuel economy.

Another potential area for development is the modeling of supply side behavior. Many studies (especially discrete choice models) simply settle with assuming a price setting oligopoly on the supply side. The standard still remains that vehicle characteristics are taken as given, and not a result of optimizing behavior by producers. Often, the most effort in modeling the supply side dynamics is put in when it comes to papers comparing the welfare gains and losses of different policies to reduce gasoline use. (e.g. Jacobsen, 2012 and Austin et al., 2005). However, the focus of these studies is rarely on the demand side, which results into the authors making the assumption of consumers being perfectly capable of correctly estimating the value of fuel economy, and thus cannot offer insight on our question of particular interest. Thus, one potential issue confounding the results is the fact that smart producers 'soften' the effect of demand behavior by e.g. pricing. Some efforts to model supply side behavior have been made in the literature. E.g. Gramlich (2009) does take a step towards combining the literature relating to product characteristic choice and that of discrete choice demand models.

Furthermore, while dynamics between the new and used vehicle markets as well as adjustments in vehicle miles driven have been taken into account in some studies, longer run effects, such as consumers changing completely their form of transportation, are often disregarded. In addition, most of the studies thus far do not take into account the option of

adopting technologies such as hybrid and electric vehicles into the choice models when studying consumers' appetite for fuel economy. Naturally, incorporating the longer run dynamic effects concerns mostly the studies that attempt to simulate future market directions with given gasoline prices. However, many studies in the current literature tend to only give short-term insight into the vehicle market and gasoline price dynamics.

#### *3.3.4 A short discussion of policy implications*

As we have now reviewed the results obtained by current the literature, it will be interesting to relate the results to the discussion around alternative policies that can be employed in an attempt to optimize gasoline use. There is a vast literature on comparing the different policy approaches, but discussing that literature in length is beyond the scope of this paper. Instead, we will settle with simply relating some of the results of the earlier discussion to the common policy questions. Two specific policies have been widely discussed in the related literature mainly due to the fact that they are the ones under heated debate in the US, namely gasoline taxes and fuel economy standards.

A given policy can affect the vehicle market on two fronts, namely the by reducing the use of gasoline as well as by modifying the composition of the vehicle fleet (e.g. Goldberg, 1998; Allcott et al. 2009). Gasoline taxes are often claimed by economists to be more efficient than vehicle standards, since they not only affect the composition of the vehicle fleet, but also the amount of gasoline consumed (i.e. driving patterns). Gasoline taxes are thus said to affect behavior not only on the extensive margin, but on the intensive margin as well. However, consumer behavior related to assessing upfront and user costs plays a role in assessing the effects of different policies – it partly determines market responses to each policy. Indeed, if consumers undervalue the future user costs of their vehicles, their extensive margin response to gasoline taxes is not likely to be optimal. This is the main argument for the use of paternalistic policies such as fuel economy standards, or alternatively higher taxes on the purchasing price of lower fuel economy vehicle. The issue indeed is that if higher gasoline prices do not induce a substantial enough reaction in the vehicle market, then 'assistance' from policies addressing directly the composition of the vehicle fleet could be warranted. (E.g. West , 2004; Allcott, 2009).

While many of the studies discussed above simply estimate automobile demand parameters, some do conduct simulations or use counterfactuals to determine the impact of

chosen policies. Some simply sketch some calculations on the sizes of the possible effects, given the parameters estimated. A typical approach is to estimate an equilibrium model containing a discrete choice demand model, and then simulating on counterfactuals (non-existing policy or different policy) to determine the impact of a given policy. (E.g. Goldberg, 1998)

What does the literature say on the effectiveness of different policies? As stated by Klier et al. (2008) and Austin et al. (2005), the welfare comparisons between command-and-control policies such as the CAFE standards and gasoline taxes depend on the effect of changes in gasoline prices in the demand for fuel economy. Our general conclusion that consumers respond only to some extent to changes in gasoline prices in terms of fuel economy would suggest that the policy effects of gasoline taxes would be limited. Klier et al. (2008) find that a one-dollar increase in the price of gasoline would only increase fuel efficiency of new vehicles by only 0.5-1 miles per gallon. Similarly, Goldberg (1998) finds that while consumers do adjust their purchases to changes in gasoline prices, taxes would have to double the price of gasoline in order to achieve the same fuel savings as the US CAFE standards do. Allcott et al. (2009, 2010) find that consumers underweight future costs of use and thus conclude that this result indeed supports the use of paternalistic policies, such as the US CAFE standards to increase average fuel economy.

When it comes to the intensive margin responses to gasoline price changes, Goldberg (1998) estimates a nested logit model and integrates the choice of miles driven into the model. Her results suggest that elasticity of 'demand' for miles driven with respect to the gas prices is small or even zero. West (2002) estimates a similar joint model, but her findings indicate the opposite - that the elasticity of demand for vehicle miles driven with respect to vehicle operating costs is between -1.03 and -0.87. Bento et al. (2009) obtain a VMT elasticity of gasoline prices of -0.34. However, the authors note that disaggregate level studies such as theirs tend to find higher VMT elasticities than aggregate time series studies, and thus imply that the elasticity could actually be biased upwards in absolute value.

#### **4 Application to the Finnish vehicle market**

After having discussed the existing literature on consumer fuel economy choices and responses to gasoline price changes, we will now implement the methods discussed to the

Finnish vehicle market with the aim of extracting a measure for consumer valuation of fuel economy. Our model has its roots in the methods developed by Berry (1994) and we will follow quite closely the specification implemented especially by Allcott et al. (2010, 2011). As discussed previously, the literature thus far has been quite inconclusive as to whether consumers are actually underweighting their fuel costs. While we aim to shed some additional light on the issue when it comes to the Finnish vehicle market, we conclude that the lack of comprehensive and high quality data is a major issue in our study. More research will thus be needed to obtain conclusive results on the issue.

#### 4.1 Modeling choices

This section describes the model to be estimated in the empirical study. The groundwork for the estimation of a discrete vehicle choice model was laid in Section 3.1., which described in detail the methods and estimation issues faced when estimating automobile demand parameters. We will thus now concentrate on presenting our own application of the methods described there, referring to the literature review when necessary.

Our utility specification is similar to that of Berry (1994) and Berry et al. (1995) presented in Section 3.1.3. The utility for a consumer  $i$  from a vehicle  $j$  at year  $t$  is defined by the set of vehicle characteristics  $x_{jt}$  and vehicle costs, which are the sum of vehicle price  $p_{jt}$  and user costs  $f_{jt}$ , which we assume to consist of future fuel costs discounted to the present moment.

$$u_{ijt} = x_{jt}\beta - \alpha(p_{jt} + f_{jt}) + \xi_{jt} + \varepsilon_{ij}$$

The term  $\xi_j$  captures the utility that is acquired by consumers from vehicle  $j$  but is unobserved by the econometrist. The addition of  $\xi_j$  is crucial. As noted by Berry et al. (1995), when using aggregate level data, if “structural” disturbance’, captured by the vehicle-specific mean unobserved component, is assumed away, then any discrepancies between the model predictions and the data can be explained only as sampling error. Indeed, in our model, there are likely to be vehicle characteristics known to both the consumer and the producer but that are unobservable or unquantifiable (e.g. brand value), and without the vehicle-specific error term these would be assumed away.

We thus model consumer utility with a random utility model where  $x_{jt}\beta - \alpha(p_{jt} + f_{jt}) + \xi_j$  is the mean, deterministic part of utility and  $\varepsilon_{ij}$  captures a random, consumer-specific part

of utility. In the next section we will define the characteristics of the distribution of  $\varepsilon_{ij}$ . The fact that we have to rely on a simplified distribution of the random term  $\varepsilon_{ij}$  is caused by the lack of consumer level data. If we had micro-level data on vehicle purchases including vehicle specific as well as consumer specific data, we would be able use that data to account for consumer heterogeneity, and thus wouldn't have to make subjective assumptions on the distribution.

In addition to defining the distributional characteristics of  $\varepsilon_{ij}$ , in the following sections we will tackle some of the issues related to estimating a discrete choice model of automobile demand. Most of the issues were already discussed in the literature review, and thus the following sections will mostly concentrate on the solution adopted in this study.

#### *4.1.1 Substitution patterns and consumer heterogeneity*

Due to the limitations related to the simple multinomial logit described in section 3.1.2, we employ the nested logit when estimating our model of the Finnish vehicle market. The main reason for opting nested logit instead of multinomial logit is the fact that the error terms  $\varepsilon_{ij}$  between certain alternatives in our model are likely to be correlated, which violates the IIA assumption made by multinomial logit. We thus divide the vehicles into  $G + 1$  mutually exclusive and exhaustive nests,  $g = 0, 1, \dots, G$ , each containing vehicles belonging to the same vehicle size class, inside which the error terms of alternative vehicles are allowed to be correlated. The vehicles belonging to the same nest can be considered substitutes. The composition of nests will be more closely discussed in section 4.2. Naturally, one must bear in mind that while nested logit is more flexible than multinomial logit, the way in which the error terms are allowed to be correlated is still quite restricted in the nested logit framework. In particular, it assumes that preferences for fuel economy are constant across the population of consumers, which is a quite restrictive assumption considering the actual vehicle market.

We will now follow Berry's (1994) presentation for obtaining the mean utility levels as functions of observed market shares in a nested logit framework. An integral part of the method described by Berry (1994) is the inversion of the market share function described in section 3.2.1, which allows us to apply linear instrumental variables methods when estimating our model. (The endogeneity issues are more closely discussed in the next section.) As Berry (1994) notes, when nested logit is employed, the error term  $\varepsilon_{ij}$  is replaced with the nested

logit error term  $\bar{\varepsilon}_{ij}$ , which consists of  $\zeta_{ig}$ , a shock common to all vehicles inside a nest  $g$ , as well as  $\varepsilon_{ij}$  unique for each vehicle. Thus the utility becomes (the time subscript has been left out for simplicity of presentation):

$$u_{ij} = x_j\beta - \alpha(p_j + f_j) + \xi_j + \zeta_{ig} + (1 - \sigma)\varepsilon_{ij}$$

where  $\sigma$  is a parameter to be estimated taking values  $0 \leq \sigma < 1$  and determines the distribution function of  $\zeta_{ig}$ , i.e. how the error terms between vehicles inside a nest are correlated. In Appendix B we derived the expression for the choice probability for multinomial logit. Using the same logic a corresponding expression for nested logit can be derived, is as follows (e.g. Train, 2003; Berry, 1994):

$$P_j = \zeta_j(\mathbf{V}, \sigma) = \frac{e^{V_j/(1-\sigma)}}{D_g^\sigma [\sum_g (D_g^{(1-\sigma)})]}$$

where  $V_j = x_j\beta - \alpha(p_j + f_j) + \xi_j$  is the mean utility from vehicle  $j$  and

$$D_g = \sum_{j \in g} e^{V_j/(1-\sigma)}$$

Now by assuming  $V_0 = 0$  and the outside good to be the only member of  $G_0$ , taking logarithms on both sides and some manipulation, as well as inverting  $\zeta_j(\mathbf{V}, \sigma)$  as described in Section 3.2.1. (see Berry, 1994), the expression becomes:

$$\ln(s_j) - \ln(s_0) = x_j\beta - \alpha(p_j + f_j) + \sigma \ln(\bar{s}_{j/g}) + \xi_j$$

Now the term  $\sigma$  is referred to as the inclusive value term. As already mentioned, it measures the correlation between the error terms of different vehicles inside the same nest. For our model to be consistent with utility maximization, the inclusive value term must be between 0 and 1. The closer the value is to 1, the more the error terms of the vehicles inside the nests are correlated. On the other hand, if  $\sigma = 0$ , there is no correlation and simple multinomial logit can be employed. In our model, the term  $\sigma$  is assumed to be fixed between consumers, meaning that the correlations taking place between vehicles inside a particular nest are similar between consumers. Were micro level data available on the

characteristics of each consumer, we could construct  $\sigma$  such that it could, for instance, be an exponential transformation of a vector of vehicle characteristics (Train, 2003, 85).

#### 4.1.2 Price endogeneity

As explained at length in Section 3.2.1, the inclusion of  $\xi_j$  introduces the simultaneity problem familiar in demand models even for homogenous goods, i.e. that the price variable is correlated with the error term. As noted by Sawhill (2008), the intuition behind this assumption is the fact that producers consider all the observed and unobserved attributes of the vehicle when setting prices. If unaccounted for, the estimated model might give counterintuitive results, such as a positive coefficient for price. (Allcott et al., 2010). Furthermore, since our estimation technique involves comparing the coefficients for price and the lifetime fuel costs, it is important that the coefficient of price is not distorted by endogeneity. Fortunately our model allows us to directly apply instrumental variables methods to account for the endogeneity of price since price enters the equation to be estimated in a linear fashion. We adopt the strategy used by Berry et al. (1995) where vehicle characteristics, their sums over the same firm and their sums over all vehicles available at a particular year are used as potential instruments. For the  $k^{\text{th}}$  characteristic  $x_{kj}$  of vehicle  $j$  produced by firm  $f$ , the potential instruments included are

$$x_{kj}, \sum_{r \neq j, r \in \mathfrak{S}_f} x_{rk}, \sum_{r \neq j, r \notin \mathfrak{S}_f} x_{rk}$$

where  $\mathfrak{S}_f$  is the set of vehicles belonging to firm  $f$ . As noted by Berry et al. (1995), since one of the vehicle characteristics is a constant term, the numbers of own-firm and rival firm products also become potential instruments.

The intuition behind these instruments for price is explained by Berry et al. (1995) and Sawhill (2008). Vehicle prices can be thought of as the sum of the marginal cost of production and a mark-up. Thus an instrument correlated with either of the two but uncorrelated with the mean utility term  $\xi_j$  could solve the endogeneity problem. The instruments developed by Berry et al. (1995) and described above indeed are designed to correlate with the mark-up. If we assume oligopoly pricing (which is a plausible description of the vehicle market), the products that have more close substitutes have lower mark-ups. Furthermore, automobile manufacturers may produce vehicles that are substitutes to each



other, and these substitutes are likely to have different effects on the mark-up compared to rival-firm products. The above-mentioned instruments are thus designed to capture the amount own-firm and rival firm competition. Variation in the instruments between vehicles results from the fact that the instruments exclude own-vehicle characteristics or include different own-firm products. The instruments have to be mean independent of  $\xi_j$  and thus we need to assume that they are not correlated with unobservable product quality.

We make one addition to the instruments used by Berry et al. (1995) and Sawhill (2008). We also include the sum of a characteristic  $k$  over vehicles belonging to the same nest as a vehicle (excluding own-vehicle characteristics):

$$\sum_{r \neq j, r \in \mathfrak{N}_n} x_{rk}$$

where  $\mathfrak{N}_n$  is the set of vehicles belonging to the nest  $n$ . We considered that as the nests are designed to contain the closest substitutes for each vehicle, the sum of characteristics over a nest should correlate with the amount of close competition with a particular vehicle and thus the mark-up included in the price of a vehicle.

The final set of instruments included in our model are the sums over own-nest vehicles of fuel consumption, mass, power, number of seats and length as well as the sums over own-firm of fuel consumption, power and length. The set of instruments was chosen due to their significance in determining real price movements. The results from regressing price over these instruments can be found in Table 2. We found that additional instruments did not improve the explanatory power and were thus left out. Indeed, some of the potential were highly correlated. The same conclusion was made by Berry et al. (1995), and the authors finally included only 15 demand side instruments in their model.

#### 4.1.3 *The final model*

Our final model thus estimates the effects of price and fuel economy on the markets shares of specific vehicles while taking into account the endogeneity of price and the fact that there may be some correlation between the error terms of similar vehicles. Yearly dummies are included to the model to be estimated, since they account for the market share of the outside good  $\ln(s_0)$ , which can thus be left out. The fact that we estimate the model with panel data

allows us separate the vehicle-specific mean utility  $\xi_{jt}$  into  $\varphi_j$ , a vehicle-specific but time constant term as well as  $\bar{\xi}_{jt}$ . The mark-model fixed effect  $\varphi_j$  captures all the other characteristics and quality of a vehicle besides price and life-time fuel costs (which are our characteristics of interest) and thus saves us the trouble of adding any other vehicle characteristics  $x_{jt}$  to the model. The final model to be estimated is thus:

$$\ln(s_{jt}) = -\alpha p_{jt} - \gamma f_{jt} + \sigma \ln(\bar{s}_{j|gt}) + \tau_t + \varphi_j + \bar{\xi}_{jt}$$

where  $p$  is instrumented by vehicle characteristics, their sums over own-firm vehicles and rival firm vehicles. As mentioned, the key characteristic of our model are the coefficients  $\alpha$  and  $\gamma$ . We give separate coefficient names for price and lifetime fuel economy to clarify the upcoming discussion on the possible differences in them, even though in our model there actually ‘should’ be only one cost coefficient. If consumers behave in a time-consistent manner, the coefficients should be equal (or their ratio should be equal to 1). Indeed, our null hypothesis is that  $\alpha = \gamma$ .  $\alpha > \gamma$  on the other hand would indicate that consumers do not fully take into account the future fuel costs at the time purchase.

An integral part of our estimation method is the fact that we use panel data to estimate the model and are thus able to exploit make-model fixed effects. As noted by Allcott et al. (2011), with cross-sectional data one has to correctly model all relevant vehicle characteristics affecting consumer utility. However, entering many vehicle characteristics into the equation to be estimated does cause some problems due to the fact that many characteristics are highly correlated, and thus any model comprising different vehicle characteristics is likely to suffer from multicollinearity. For instance, vehicle weight and fuel consumption are mechanically correlated. (This is a conclusion we draw also in section 4.2.2. discussing our data set). Thus, as noted by Allcott et al. (2011), the correlation between characteristics such as weight, horse power and fuel consumption make it difficult to separately estimate preferences for each. Atkinson et al. (1984) found that cross-sectional estimation of vehicle demand can result into a counterintuitive sign on fuel economy (i.e. that a higher fuel consumption would actually be preferable for consumers). Thus, panel data allows us to control for all other vehicle characteristics with fixed effects and enter estimated lifetime fuel costs as the only vehicle characteristic, in addition to price, to the equation to be estimated.

As stated by Sawhill (2008), most of the heterogeneous product demand literature considers price to be the only endogenous variable. However, other vehicle characteristics, such as fuel economy, are likely to be correlated with the unobserved characteristics as well (e.g. Allcott et al. 2011). Another upside of exploiting mark-model fixed effects is the fact they mitigate this problem, again since it controls for the vehicle-specific, time-constant part of utility. We thus we employ a similar method with Allcott et al. (2011) in taking into account the endogeneity of fuel economy. However, whereas the authors are able to use model-year fixed effects, we have to content with mark-model fixed effects due to data restrictions. The problem with this approach is the fact that over our data period of seven years alterations have often been made to models (e.g. Toyota Corolla has changed considerably over the years), and thus the part of the utility that is fixed over time is smaller and  $\varphi_j$  does not necessarily capture all relevant vehicle characteristics.

## **4.2 Data and industry**

### *4.2.1 Overall data description*

The data used in the estimation of our model consists of all new vehicle purchases made in Finland between the years 2005 and 2011 and vehicle characteristics and prices for each year. The data used in the estimation was acquired from two main sources. The new vehicle market shares are derived from vehicle registration data acquired from Trafi (2012). The registrations are reported at model level (e.g. Honda Accord or Fiat Punto), and there are 401 make-model combinations in the data. The registration data is summarized by make and year of registration in Table 1. The characteristic and price data on the other hand was acquired from Netwheels (2012), a consultancy that maintains a database where vehicle importers update bi-annually the price and characteristic data of the new vehicles offered in Finland at that particular time. The Netwheels data reports the characteristics and prices for various trim levels for each model, and is thus more detailed than the registration data.

The two data sets had to be combined to produce the final data set used in the estimation. In the final data set, one vehicle refers to a make-model combination due to the fact that the registrations are reported only at that level. Since the characteristics and prices are reported at the trim level, they had to be averaged over each make-model combination. Furthermore, there was some mismatch in the data since the Netwheels (2012) data set contains only new vehicles offered in Finland and the registration data contains some individually imported

models including vehicles that are clearly not new at the time of registration. The mismatch was dealt with by deleting registrations of vehicles that were clearly not new at the time of the registration (e.g. Ford Mustang), since the data is meant to concern only new vehicle registrations in the first place.

The registration data was yearly data whereas the Netwheels data was bi-annual. The registrations for a particular year were combined with the Netwheels characteristic and price data dated at January 1<sup>st</sup> that same year. For some vehicles the characteristics data of July 1<sup>st</sup> was used due to the fact that they had become available for sale later in the year and thus appeared only in the 'mid-year' data. For some vehicles that had become available late in the year that characteristics data dated 1<sup>st</sup> of January the next year was used. The problem with this practice is the fact that the after-tax prices of most vehicles changed in 2008 due to the change in vehicle taxation, and thus using the same data for the prices does not account for this change. There were about 20 make-models that have the same price between 2007 and 2008 in our final data. The prices in the data are list prices quoted by the importers and transformed into 2005 prices by using the consumer price index offered by Statistics Agency in Finland (SVT 2012b). The use of market shares instead of units sold in the equation helps control for the total sales during that year. Descriptive statistics on the data can be found in Table 4. The average price (transformed to 2005 prices) of a vehicle over the period is 49 093 euros and the average fuel consumption is 8.29 liters per 100 kilometers. The average amount of vehicles registered of a particular model per year is 439.

As described in Section 4.1.1., the vehicles were divided into nests each containing vehicles that can be assumed to be close substitutes. The nests used in our study are the British vehicle size classes. The reason for using the British vehicle size classes instead of the European ones is their easier availability on the Internet (e.g. Wikipedia). This choice of classification is unlikely to affect the estimation results since the size classes are quite similar in content and differ mostly by name. A listing of the nests can be found in Table 5. The use of vehicle size classes to depict substitution patterns between vehicles seems quite intuitive, since a consumer pondering the purchase of a vehicle is likely to see e.g. 2 mid-size cross-over SUV's as close substitutes for each other, whereas e.g. a super mini might not answer to the needs of the same consumer and not be seen as an close substitute.

Data quality was somewhat of a problem especially when it comes to the first years in the sample, but the quality of the data improved towards the latter part of the period. For instance, the characteristics data lacked some characteristics (e.g. torque) completely for 2005 and was incomplete for some other characteristics. Furthermore, the vehicle registrations data for 2005 and 2006 contained some registrations with ambiguous models, such as ‘Ferrari, unspecified’. Fortunately these concerned vehicles with very small markets shares (e.g. 1 vehicle registered per year). Furthermore, some mark-model combinations in the registrations data were unrecognizable as such, but could be associated with some existing model (e.g. Kia Ed probably referred to Kia Cee’d). The fact that registrations were reported only at make-model level also meant that some aspects of the more specific, trim-level characteristics data were lost. For instance, a particular make-model combination can contain trims with either manual or automatic transmission. However, since characteristics had to be averaged over make-model combinations, transmission type couldn’t be taken into account as a variable. The same problem applies to also whether a vehicle uses diesel or gasoline. Furthermore, many mark-model combinations can contain different body types, such as sedans or station wagons.

One drawback related to the time series dimension of the data is the fact that since the registered quantities are reported only at the yearly level and no model-years are reported, we are able to use fixed-effects only at the make-model levels over the period of 2005-2011. The problem with make-model fixed effects over such a long period is that models with the same nameplate can undergo quite significant changes over time. A good example of this is Toyota Corolla. Thus model-year fixed effects could be more adept in capturing the unobserved quality of a vehicle as it is more likely to stay constant inside a model-year than for a particular model name over the years. The section discussing our estimation results illustrates well the problems with make-model level yearly fixed effects. Furthermore, due the yearly frequency of our registration data the effects of intra-year gasoline price variations cannot be taken into account, and gasoline price variations are reduced to yearly averages. Indeed, our observation period of seven years does not produce very significant changes in gasoline prices. Figure 2 illustrates how gasoline prices have developed over the observation period.

#### 4.2.2 *The estimated lifetime fuel cost*

To obtain an estimate of the lifetime fuel cost of a vehicle, we need data and/or assumptions on vehicle fuel consumption, vehicle miles driven during each year of use,

vehicle life, future fuel costs as well as the discount rate used by consumers to estimate future costs. How we define the expected lifetime fuel cost matters quite a lot for the conclusions we are able to draw from the comparisons of the coefficients  $\alpha$  and  $\gamma$ . Lifetime fuel costs are calculated as:

$$f_{jt} = \sum_{s=t+1}^{t+a} \delta^{s-t} \times g_s \times fc_{js} \times km_{ns}$$

where  $t$  is the year of purchase and  $a$  is the average scrappage year,  $g_s$  is the average gasoline price for year  $s$ ,  $fc_{js}$  is the fuel consumption of model  $j$  in year  $s$  and  $km_{ns}$  is the amount of kilometers driven by a model  $j$  belonging to the nest  $n$  on the  $s$ th year of its life.  $\delta$  is the discount factor.

We use data from A-Katsastus (2012), a Finnish company specialized in conducting MOT tests, to estimate the kilometers driven per year. A-Katsastus publishes data on average odometer readings of the vehicles inspected by make-model and the year of purchase of the vehicle. Thus we obtained a sample of data on the average vehicle kilometers driven per year, given the vehicles age. The sample contained vehicles inspected in 2011 and purchased in 2008 and 2006-1998. Only models for which at least 100 vehicles were inspected during 2011 were included in the data. We hypothesized that the type of the vehicle (vehicle size class) and its age would be the main determinants of the vehicle miles driven of a given vehicle during one year, which was confirmed by the data. We thus calculated an ‘initial’ kilometers driven per year specific to each vehicle size class, and assumed the kilometers driven to decline as the vehicle got older from that ‘initial’ figure. Since the average age of vehicles in a certain vehicle size class was likely to affect the average vehicle kilometers driven for that class, we calculated the average rate of decline for each of the years in the life of a vehicle and used that rate to normalize the yearly vehicle kilometers into representing the first year after the purchase of the vehicle. It was assumed that the declining trend in vehicle miles driven started only in the fourth year of the life of the vehicle. Furthermore, even though data was available only for 13 year-old vehicles and under, the same rate of decline was assumed to continue until the rest of the life of the vehicle.

Data on average vehicle life was acquired from Autoalan tiedotuskeskus (2012a) and was 19.1 years for the period of interest. To calculate the cost of driving 100 kilometers with each

model in the data, the fuel consumption given by the Netwheels (2012) dataset was multiplied by the average real price of gasoline for a given year. Thus, the cost varied year to year due to the changes in fuel consumption as well as in gasoline prices. Of course, gasoline prices are not likely to stay constant during the rest of the useful life of a vehicle and thus we had to make an assumption about the expectations made by consumers of future gasoline price movements. A common assumption made in related literature when estimating the future discounted fuel cost of a vehicle is that fuel prices follow a random walk (Allcott et al., 2010; Klier et al., 2008). This assumption allows the econometrist to use the current price of gasoline at the particular point in time to estimate consumers' expected price for all future points in time, since all variation in the price can be regarded as white noise. One could argue that oil price and thus fuel price expectation would with move with the economic cycle, but it also seems plausible that the average consumer isn't able to make these predictions and thus the fuel price follows a random walk from his point of view. In our study, we assumed the expected gasoline prices to follow a random walk from the point of view of the consumer. Oil price futures could be a potential way to model gas price expectations, but they tend to actually be quite close to the spot price of oil at a given time.

The choice of the discount rate used by consumers when estimating lifetime fuel costs of a vehicle is quite arbitrary. However, one can make assumptions on plausible discount rates based on information on the risk-free rate of return and market interests rates for e.g. car loans. We adopt from previous studies (Allcott et al. 2011; Sawhill, 2008) the use of 5% as an appropriate discount rate. The rate is above the long term average of the risk-free rate of return and somewhat below the average interest rate on consumer loans in Finland (Suomen Pankki, 2012). We will test the sensitivity if our final results on the interest rate. Indeed, if reformulated our research question effectively asks which is the appropriate discount rate consistent with observed purchases of vehicles.

Of course, our model of the lifetime fuel cost of a vehicle is a simplified one and relies on a very limited set of data. More sophisticated assumptions could have been made especially about the driving pattern of consumers. Sawhill (2008), for instance, allows consumers to adjust their driving patterns to changes in gasoline prices. He fits a model of gas price evolution,  $\Delta p_t^g = \phi \Delta p_{t-1}^g + u_t$ , where  $u_t$  is a white noise process, to the historical US gas prices and defines the miles driven to respond to the changes depicted by the model. When estimating our model we noticed that small adjustments in the assumptions did not

considerably affect our final results. Indeed, in section 4.3.2 we will discuss the sensitivity of our model to the assumptions made above. One must keep in mind however that, as stated by Allcott et al. (2011), measurement error in our lifetime fuel cost variable would bias its coefficient towards zero and thus make it seem like consumers would be underweighting fuel costs compared to price more than they actually do.

#### *4.2.3 Reduced form data and industry analysis*

Looking at the general trends in the Finnish vehicle market, the 2008 policy change favoring the purchases of high fuel economy vehicles has been a quite significant determinant of market developments. In 2008 vehicle purchase taxation changed such that the tax rate is determined by the amount of CO<sub>2</sub> emitted by the vehicle per kilometer. Indeed, as a result of the change the after-tax prices of low-emission vehicles decreased and those of the high-emission vehicles increased. Another change in the taxation took place in 2012, when additional reductions in the vehicle purchase tax rate was made for vehicles emitting less than 100 grams of CO<sub>2</sub> per kilometer and increased for all other vehicles. (Autoalan tiedotuskeskus, 2012b).

Figure 3 shows that the average CO<sub>2</sub> emissions (which go hand in hand with fuel economy) in Finland have been on a clearly decreasing trend since 2008 when the new policy took effect. Slight increases in the average emissions of newly purchased vehicle were however witnessed in the beginning of 2012 due to the fact that the taxation was tightened in April 2012. Figure 4 on also shows how average fuel efficiency dropped dramatically in 2008. Of course, gasoline prices also happened to peak in 2008 – indeed, the policy change makes it harder to observe and extract the impact of higher gasoline prices on vehicle purchases from time series data on vehicle characteristics from recent years. Figure 5 on the other hand shows that as fuel efficiency has improved considerably beginning in 2008, the trade-off between fuel efficiency and other characteristics has improved as well. E.g. average vehicle mass and power haven't deteriorated considerably after 2008, even though they are usually associated with higher fuel consumption. Thus the improvements in vehicle fuel efficiency haven't taken place at the cost of other characteristics, although the upward trend in vehicle mass and power has actually halted.

Trends in vehicle registrations and prices seem to follow economic cycles. During economic downturns vehicles purchase decisions seem to be put off until less turbulent times



for the economy. Indeed, Figure 7 shows that even though the number of households has increased in Finland over the last 20 years, the number of registered vehicles has fluctuated considerably. The effect of the economic downturns of the beginning of the 1990's, 2000's and the end of 2000's can be witnessed in the registrations data. When it comes to the types of vehicles registered, family cars (small and large) are by far the most registered vehicle size class, as shown by Figure 9. On the other hand among the other size classes SUV's have had a steady upward trend in registrations. Figure 8 on the other hand shows that Toyota and Volkswagen have dominated the Finnish vehicle market in terms of market shares.

When it comes to vehicle characteristics in our data set, the immediate observation is that vehicle characteristics, as one would assume, are highly correlated. Table 3 shows that especially the fuel efficiency of a vehicle is highly correlated with price and other characteristics related to engine performance and vehicle size. The positive correlation between price and fuel consumption can seem counterintuitive considering the starting point of our study – of consumers were perfectly rational fuel consumption is associated with higher user costs of a vehicle and thus should be associated with lower prices. However, fuel consumption is highly correlated with other desirable characteristics. This fact supports the choice of panel data estimation methods, as discussed in Section 4.1.3.

### **4.3 Estimation and results**

#### *4.3.1 Baseline nested logit and multinomial logit specifications*

The baseline model is estimated as an instrumental variables fixed effects regression, where fixed effects are taken over 401 make-model combinations. Price is instrumented as explained in detail in section 4.1.2 and the second stage is a fixed effects regression of the logarithm of market share. Independent variables include price (instrumented), the logarithm of nest share, lifetime fuel costs and yearly dummies. The variables and summary statistics are listed in Table 4. The baseline estimation thus takes into account price endogeneity and models substitution patterns with nested logit.

The results obtained from the baseline estimation can be found in Table 6. Table 7 on the other hand contains a summary of the coefficients obtained from the baseline as well as some alternative estimations. In the baseline model the coefficients of (real) vehicle price, lifetime fuel cost are significant. The coefficient of the logarithm of nest share, which is the inclusive

value term of our nested logit specification, falls between 0 and 1 as expected. The fact that the inclusive value term is close to one in all the specifications listed in Table 7 would seem to indicate that our choice of nested logit instead of multinomial logit to model substitution is correct. This means that the error terms of vehicles inside the same nest seem to be correlated and thus (quite intuitively) indicates that some vehicles are indeed closer substitutes than others.

The most striking result from our baseline model is the fact that the coefficient of lifetime fuel cost is positive, and thus indicates counter intuitively that a higher lifetime fuel cost would actually increase the utility obtained from the purchase of a vehicle. Estimating the model with the cost of driving 100 kilometers (i.e. the price of gasoline on the year of the purchase of the vehicle times its fuel consumption per 100 km) instead of our measure of lifetime fuel costs also gives a positive sign for the coefficient of fuel costs, and thus the seemingly positive impact on consumer utility of higher fuel costs seems to result from differences in fuel consumption and not on the assumptions made when transforming it into *lifetime* fuel costs.

However, the result alone hardly allows us to draw the conclusion that consumers do not care at all about fuel costs when purchasing vehicles. Indeed, the counterintuitive sign for fuel consumption and costs is likely to be a result of the fact that vehicle characteristics are highly correlated, and that our panel data approach of using yearly fixed effects for make-model combinations is probably not strong enough to control for all the other characteristics and the unobserved quality of the vehicle besides lifetime fuel costs and price. Indeed, higher fuel consumption is closely and positively correlated with other desirable vehicle characteristics. Due to the correlation between vehicle characteristics, fuel economy is likely to be endogenous, since a part of the unobserved vehicle quality is left in the error term despite the use of make-model yearly fixed effects, which makes the error term correlated with fuel economy. As discussed in Section 3.2.2., Gramlich (2009) argues that the parameter estimates obtained when not accounting for the endogeneity of fuel economy are biased downwards, which could thus weight on the ratio of interest  $\gamma / \alpha$  in our model. Furthermore, as stated by Allcott et al. (2010), one symptom of endogeneity are counterintuitive signs on (e.g. price) coefficients.

Furthermore, estimating the model as a multinomial logit model and thus leaving out the logarithm of nest share actually does give the ‘expected’ sign for the lifetime fuel cost variable, as can be seen in the column 2 of Table 7. The problem with the nested logit approach is the fact that the logarithm of nest share is highly correlated with the logarithm of market share and thus dominates the estimated model. One can thus draw the conclusion that the positive coefficient of the lifetime fuel cost variable does not seem to be a robust result across specifications. However, the ratio of interest  $\gamma / \alpha$  seems to be well under 1 for both the nested logit and multinomial logit models, which would indicate an underweight for the discounted lifetime fuel costs compared to the upfront price paid from a vehicle. The ratio is higher in the case of multinomial logit, which is counterintuitive since multinomial logit should overstate the substitutability between vehicles. This same result has been found by Allcott et al. (2010). The multinomial logit specification naturally suffers from lower R-squared since one highly significant explanatory variable is left out of the model. Furthermore, the coefficients for price and lifetime fuel cost are significant at the 90% level only if mass and power are added to the model as explanatory variables, which indicates the weaknesses of the make-model yearly fixed effects in controlling for all other vehicle characteristics and quality besides fuel costs and price.

Our baseline model assumed price endogeneity and thus employs instrumental variables. In column 5 of Table 4 we have estimated the model without the assumption of price endogeneity. The coefficients of both price and lifetime fuel costs are lower than in our baseline model, but the ratio  $\gamma / \alpha$  however is slightly higher. The fact that the coefficient of real price does not seem to differ much from the baseline, instrumented price specification seems to indicate that price endogeneity is not the most severe problem in our model. Instead, the limited amount of observations and the difficulty of our model to capture all the relevant quality of a vehicle seem to distort the results much more.

Indeed, it is clear that especially the robustness issues relating to the coefficient of lifetime fuel costs reveal problems in data quality, the limited amount of data available as well as the inability of make-model level fixed effects to control for unobserved vehicle quality. However, none of the alternative specifications compared above give support to the null hypothesis of consumers being indifferent between the upfront price and the present value of lifetime fuel costs. Of course, in addition to the assumptions mentioned above, the results

depend also on other modeling choices and assumptions. The next section will discuss in more the effects of these assumptions.

#### *4.3.2 Alternative assumptions and sensitivity analysis*

Naturally, the results obtained in our baseline specification depend heavily on the assumptions made especially when constructing the lifetime fuel cost variable. The choice of discount rate use especially affects the results obtained. Indeed, our research question can actually be reformulated to asking which discount rate is consistent with consumer behavior in our model. The sensitivity of the estimation results was thus tested by estimating the model with different values for the discount rate. The discount rate that equated the coefficients for lifetime fuel costs and price was 15% for the multinomial logit model. There isn't much point in calculating the corresponding discount rate for the nested logit model due to the positive sign of the lifetime fuel cost variable in the model. The implicit discount rate for the multinomial logit model is considerably above the riskless rate of return and somewhat above the rate on a typical car loan, which is 5-10% in Finland. Indeed, as Figure 10 shows the average interest rate on consumption loans was below 7% during the period between 2005 and 2011. Thus one can question whether such high interest rates are consistent with rational decision making across time.

When constructing the lifetime fuel cost variable we also made the assumption that vehicle size class, and thus loosely the type of the vehicle, determined the amount of kilometers typically driven with a particular vehicle. (All other assumption made to construct the variable, namely those concerning the average age of scrappage and the rate of decline in the kilometers driven we considered to be constant between models.) To test the validity of this assumption, we also estimated the model with a lifetime fuel cost variable that made the same assumptions for all models about kilometers driven during the same year. This actually almost doubled the  $\gamma / \alpha$  ratio to -0.36. One must note that the sign of the coefficient of the lifetime fuel cost variable remains positive and isn't straightforward to interpret due to the problems remaining in our specification and data.

We also made an arbitrary decision about how the vehicles are divided into nests and thus about which vehicles are substitutes in the eyes of consumers. We thus estimated the model also with less detailed nests. If our baseline model included Compact crossover SUV's, Mid-size crossover SUV's and Full-size crossover SUV's as separate nests for instance, the less

detailed nesting specification had all crossover SUV's grouped in the same nest. The results from the specification with less detailed nests can be found in the column 6 of Table 7. Although the coefficients for real price and lifetime fuel costs are slightly higher in this specification, their ratio remains largely the same and thus gives no support for the null hypothesis either. The coefficients remain significant for this specification, but the coefficient for lifetime fuel costs has a positive sign.

In our baseline model price and lifetime fuel costs are the only vehicle characteristics used as explanatory variables. Indeed, our ability to include any other vehicle characteristics in the model is limited by the problem of multicollinearity. As observed in Section 4.2.2 discussing our data, vehicle characteristics seem to be highly correlated with each other, and thus adding vehicle characteristics to the equation might bias upwards the standard error of the fuel cost term making the coefficient not seem significant. Thus we originally use make-model fixed-effects to capture all other vehicle quality besides price and vehicle costs. If vehicle mass and power are added as explanatory variables to the nested logit and multinomial logit models (columns 3 and 4 in Table 7), the coefficient for lifetime fuel costs falls in both models. Therefore, also the ratio  $\gamma / \alpha$  falls. In the case of the multinomial logit model the coefficients of price and lifetime fuel cost actually become more significant when vehicle mass and power are included, contrary to what we might expect to happen when multicollinearity is an issue. The overall explanatory power of the logit model still isn't very high, however, with an overall R-squared of only 0.18. In the baseline nested logit model adding the variables does not improve the overall explanatory power of the model.

One issue that we didn't take into account in our model is the fact that vehicle taxation was altered in Finland during our period of study. The prices we use are after-tax prices and the yearly fixed effects of course account for any year-specific characteristics of the market. We could expect, for instance, that SUV's or other 'gas guzzlers' would have been more attractive to consumers in 2007 just before the change in policy. On the other hand incentives to purchase high fuel economy vehicles would have been low in the end of 2007 due to the fact that the after-tax prices decreased at the turn of the year. We did estimate the model separately for 2005-2007 and 2008-2011. The amount of observations for these shorter periods is quite low and thus the results again aren't very robust. Especially the coefficients of price and lifetime fuel costs are not significant, but the latter takes a negative sign in the model for 2005-2007. One could speculate that for the 2005-2007 period the measure of

lifetime fuel costs would actually capture the negative impact of higher costs on the utility derived from a vehicle, whereas for the latter period the measure is correlated with the after-tax price (due to the higher tax rate for lower fuel economy vehicles), and that real price would actually capture the negative effects of higher costs as well.

#### *4.3.3 Discussion of the results*

Overall one has to be quite careful in deriving definitive conclusions relating to the research questions from our model. The fact that the baseline model gives a counterintuitive sign for lifetime fuel costs is quite troubling. The result most certainly does not allow us to draw the conclusion that consumers would actually prefer higher fuel costs. First of all, the sign is not very robust in the sense that the multinomial logit specification actually does give the ‘right’ sign for the coefficient of the variable. Furthermore, higher fuel costs are tightly correlated with other desirable vehicle characteristics, and it seems that our model is unable to control for these characteristics enough to capture separately the effects of the fuel costs. For instance, the relatively high fuel consumption of a Ferrari 458 Italia is closely associated with its desirable characteristics, such as power. But if a consumer was asked to choose between two Ferrari 458 Italia’s which would be otherwise similar but have different fuel consumptions, he/she would probably choose the one with lower fuel consumption. Thus if one is successful in controlling for the ‘other’ quality of a vehicle, lower fuel consumption should be preferable. If the ‘other’ quality on the other hand isn’t controlled for well enough, the measure of fuel consumption will capture the unobserved quality as well and will seem like a desirable characteristic. A consumer would probably rather choose the Ferrari 458 Italia than a Fiat Punto, for instance, even with the higher fuel consumption. As mentioned in Section 4.1.3., Atkinson et al. (1984) discovered a similar problem, namely that the correlation between fuel economy and mass make it difficult to separately measure preferences for fuel economy in cross-sectional data and thus gives the wrong sign for fuel economy. Indeed, it seems that our panel data approach controlling for ‘other’ quality is not strong enough to eliminate the correlation problem.

Even though the robustness of our results can be questioned, none of the different specifications estimated offer particular support to our null hypothesis of consumers making optimal trade-offs between upfront costs and future costs of use. Actually, in some of our alternative specifications the coefficient of lifetime fuel costs (or simply fuel consumption)

becomes insignificant even at the 90% confidence level. Of course, this result might also be affected by the limited amount of observations in our dataset and should thus be taken with a grain of salt. Furthermore, the discount rate consistent with the modeled choices of vehicles seem quite high, and actually corresponds to those found in earlier literature studying durable good choices. Of course, as described in Section 2.3., some studies in the past literature suggest that due to the characteristics of energy efficiency investments such as automobile fuel economy, the discount rates used by rational consumer might actually be quite high (e.g. Metcalf et al., 1995). Furthermore, it is important to keep in mind that a failure in accounting for the endogeneity of fuel consumption can bias the lifetime fuel cost coefficient downwards and thus make it seem as if consumers were putting less weight on fuel costs than they actually do (Gramlich, 2009). Anyway, what we can say based on our results is that at least they do not as such give support to a 'laissez-faire' approach to vehicle fuel economy. Even though the results do not permit us to definitely conclude that consumers are myopic, the results do not rule out the possibility that paternalistic approaches to policy would be warranted.

More research is thus needed to draw any definitive conclusions on the subject. Especially a more comprehensive dataset would be warranted to increase the robustness of any results obtained on the Finnish vehicle market. As noted in Section 3.3.3., existing literature on the subject thus far has been quite inconclusive as well in the sense that different modeling assumptions have resulted in all but opposite results and conclusion about consumer valuations of fuel economy. One could say that there are two prominent approaches in the literature for obtaining a measure for the optimality of consumers' fuel economy choices. The one used by e.g. Allcott et al. (2009, 2010, 2011) as well as Sawhill (2008) employ discrete choice modeling and thus attempts to specifically measure parameters relating to consumer preferences whereas studies such as Li et al. (2009, 2012) and Busse et al. (2010, 2012) estimate 'reduced form', market-level models.

Even though the robustness of our results leaves room for improvement, they are in line with those obtained by similar studies by e.g. Allcott et al. (2011) in the sense that they don't give much support for the null hypothesis of consumers being perfectly rational in their purchases of vehicles when considering the fuel economy of a vehicle. (Actually, our model reveals an even stronger bias towards present costs than the one estimated by Allcott et al. (2011), suggesting possible identification issues in our model.) It is important to bear in mind

however that the alternative market-level approach mostly reaches the opposite conclusion, namely that gasoline prices do affect the composition of the vehicle fleet. Busse et al. (2012), for instance, find that changes in gasoline prices have a significant impact on the market shares of new vehicles with different fuel economies and are able to deduce implicit discount rates that correspond to the interest costs paid by consumers when funding their vehicle purchases. The advantage of the approach we adopted is the fact that it has potential to give a direct measure of the consumer valuation of fuel economy. Indeed, Busse et al. (2012) are forced to use demand elasticities from previous studies to obtain their estimate of the implicit discount rate. Furthermore, our approach is based on a model of discrete consumer choices and thus has more tractable micro-foundations.

On the downside, many assumption have to be made to estimate the model which are likely to affect the final results, and thus a careful sensitivity analysis is warranted to ensure the robustness of any results. Our model is likely to suffer from attenuation bias - if there is measurement error in the lifetime fuel cost variable, its coefficient would be biased towards zero. Attenuation bias thus probably contributes to the low lifetime fuel cost coefficients obtained by our model. Furthermore, as the results are highly dependent on the coefficient of price (as it is the one used to interpret that of lifetime fuel costs), correctly accounting for the endogeneity of price has a crucial role in determining the conclusions made from the results obtained. Moreover, our model does concentrate only on one aspect of gasoline price changes, namely their effect on vehicle fuel economy choices. It does not take into account the fact that gasoline price changes are likely to affect driving patterns as well. Indeed, consumers hold the real option of driving less if gasoline prices turn out high, and thus need not 'care' as much about fuel economy (e.g. Sawhill, 2008). Furthermore, our model concentrates only on the new vehicle market, and thus the effects of changes in the substitution patterns between new and used vehicles as well as vehicle scrappage are disregarded. Also the fact that producers might adjust their behavior in response to gasoline price changes can potentially affect the market outcome.

## **5 Conclusion**

The question of whether consumers are capable of making optimal trade-offs between current and future costs when purchasing vehicles has recently been discussed quite vastly in



the economic literature especially in relation the question of whether gasoline taxes or paternalistic policies such as fuel economy standards would be optimal in reducing greenhouse gas emissions from gasoline combustion by passenger cars. The background of the question is more generally in the apparently slow diffusion of seemingly cost efficient conservation technologies. Hausman (1979) was one of the first to find that consumers' purchases of durable, energy consuming goods are consistent with them being 'myopic'. In terms of economic theory this phenomenon has been explained by e.g. hyperbolic discounting, the public good nature of information on new technologies as well as flawed expectation formation in the absence of perfect information.

Looking at the previous literature on consumer valuations of fuel economy, no clear conclusions can be drawn as to whether consumers give an optimal amount of weight to gasoline prices when purchasing vehicles. Most studies seem to indicate that consumers do to some extent take into account the changes in gasoline prices, but that some stickiness in the market responses exists. However, the results obtained by the literature vary quite a lot in accordance with the different assumptions made. Indeed, there are various margins over which the behavior of consumers and producers alike is adjusted in response to gasoline prices, and different studies shed light on different potential responses. Those studies that are able to offer insight on the optimality of the weight given to vehicle lifetime fuel costs in comparison to the upfront price have obtained quite different results. The reduced form approach adopted by e.g. Busse et al. (2012) does not find signs of myopia, whereas the discrete choice approach used by e.g. Allcott et al. (2011) as well as the present study would suggest underweight on future gasoline costs.

Indeed, our empirical study does not give support to the null hypothesis of consumers weighing equally the price and the present value of lifetime fuel costs. On the contrary, our results indicate that the weight given to the present value of lifetime fuel costs would account for only a fifth of that given to price. Thus, based on our model it would seem that e.g. a hyperbolic discounting model would better describe actual consumer behavior when it comes to fuel economy investments. Another way to express the result is the that the implicit discount rates that consumers would seem to use when making fuel economy investment decision are higher than actual markets interest rates would warrant. Of course, one can question the appropriateness of these comparisons. Some studies discussed in our literature review suggest that returns on energy efficiency investments are highly uncertain and thus the

discount rates warranted to evaluate future returns could be high. Furthermore, one must keep in mind that there are several problems in our specification that might affect our results and bias them towards indicating consumer myopia and high implicit discount rates. Indeed, especially the difficulties in identifying the consumer preferences for fuel economy separate of any other correlated vehicle characteristic, the potential endogeneity of the lifetime fuel cost variable as well as attenuation bias potentially bias our results.

Our study alone does not permit us to give conclusive policy recommendations besides the fact that they do not rule out the efficiency of the current vehicle taxation policy adopted in Finland or the even more paternalistic CAFE standards in the US. More research is thus needed. In particular, many studies discussed in this paper employ aggregate level data and are forced to use simplifying assumptions to model the fact that there is quite a lot of variation in consumers' preferences regarding vehicle characteristics and fuel economy. Our nested logit approach, while relaxing some of the strict assumptions made by multinomial logit, is still quite rigid when it comes to modeling consumer heterogeneity. Using random coefficients instead of nested logit would relax the quite restrictive assumption that all consumers have the same valuation on vehicle fuel economy. However, even the random coefficients approach is forced to make assumptions on the distribution of consumer preferences over vehicles characteristics over some mean value. Thus studies using micro-level data including consumer characteristics would be warranted at least to complement the aggregate level data. Furthermore, studies taking into account a wider range of margins over which consumer and producer behavior is adjusted in response to changes in gasoline prices are warranted.

A particularly interesting aspect of fleet fuel economy policy that has been slighted in this study is the fact that older vehicles are more likely to be gas guzzlers as new. The relatively high vehicle taxes in Finland discourage consumers from purchasing new vehicles and thus shifting to models that take advantage of recent the technology development in the field. Thus in addition to using policy to encourage consumers to opt for less-consuming vehicles, another aspect of policy design is giving incentives for consumers to shift to newer and less-consuming models.

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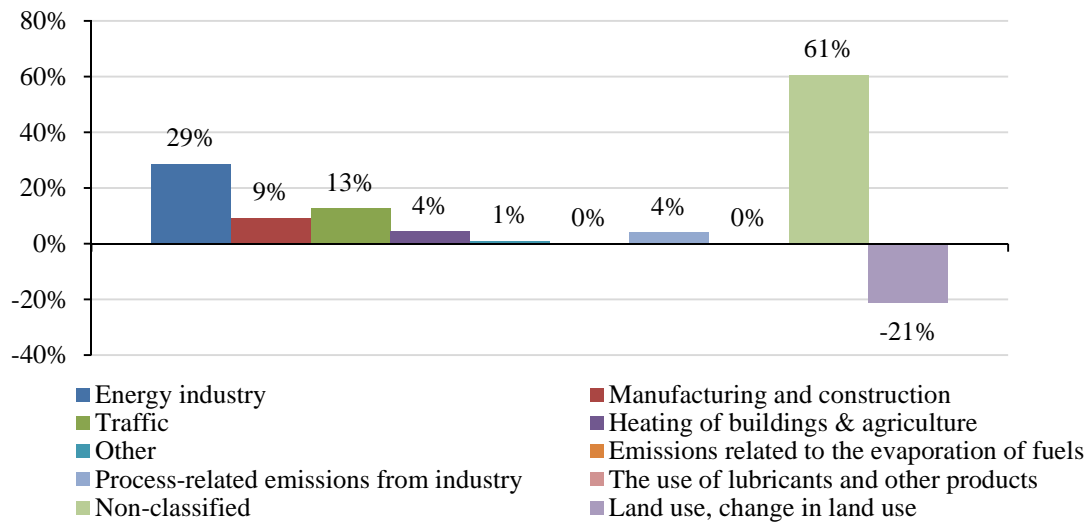
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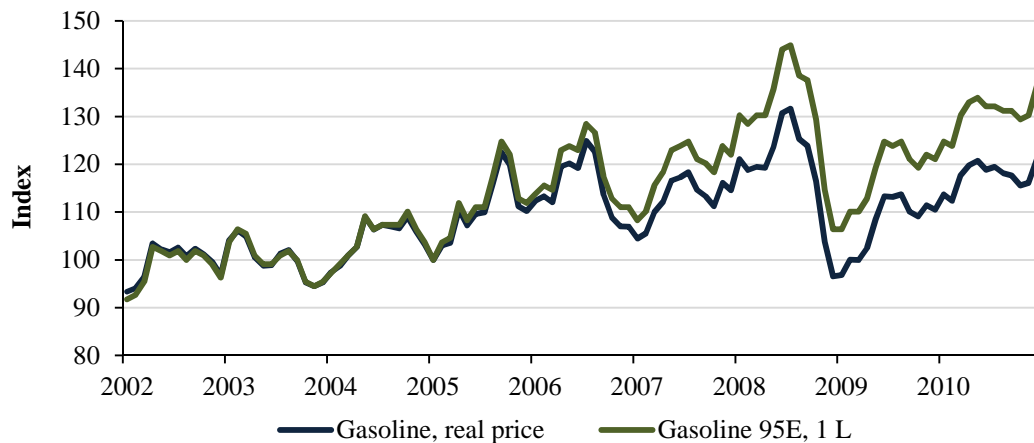
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## Figures

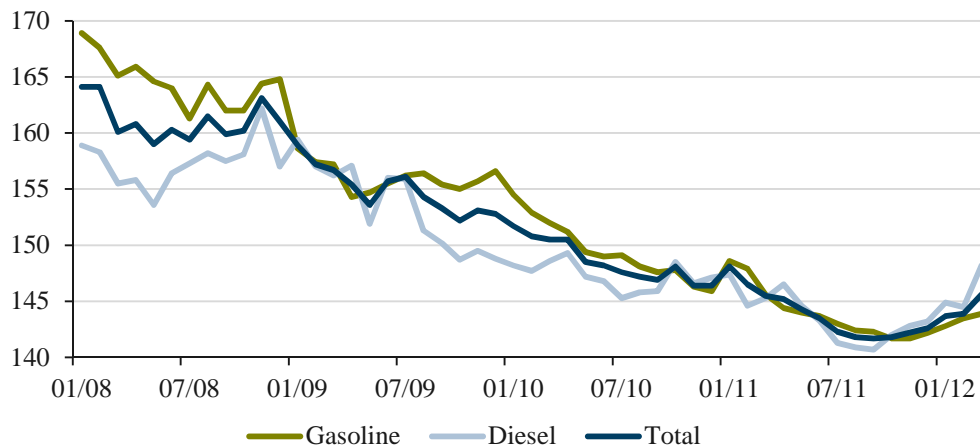
**Figure 1 Shares of CO2 emissions in Finland by industry, 2010 (SVT 2012a)**



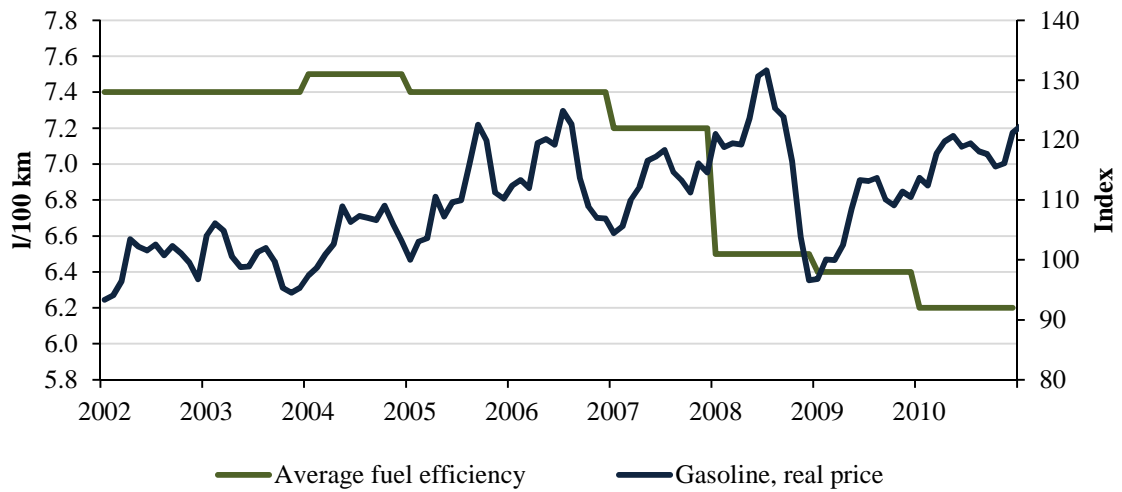
**Figure 2 Gasoline prices in Finland in 2002–2010 (Autoalan tiedotuskeskus 2012c)**



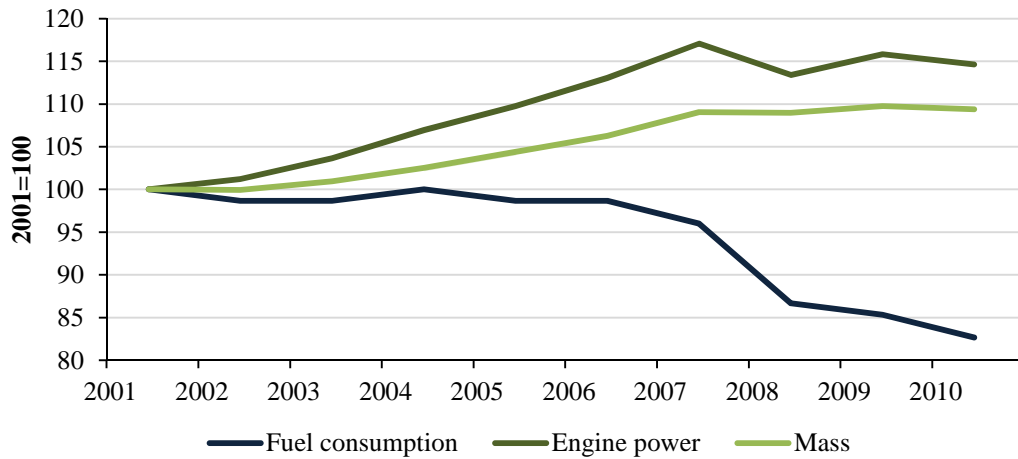
**Figure 3 Average Co2 emissions of new vehicles in Finland 2008–2012 (Trafi 2012c)**



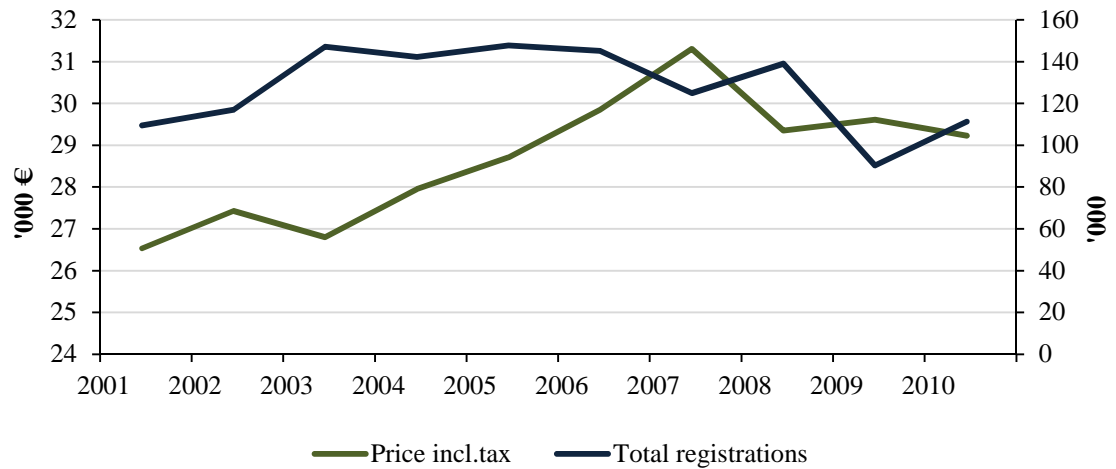
**Figure 4 Average fuel efficiency after 2002 in Finland (ICCT 2011)**



**Figure 5 Average vehicle characteristics in Finland 2001-2010 (ICCT 2011)**

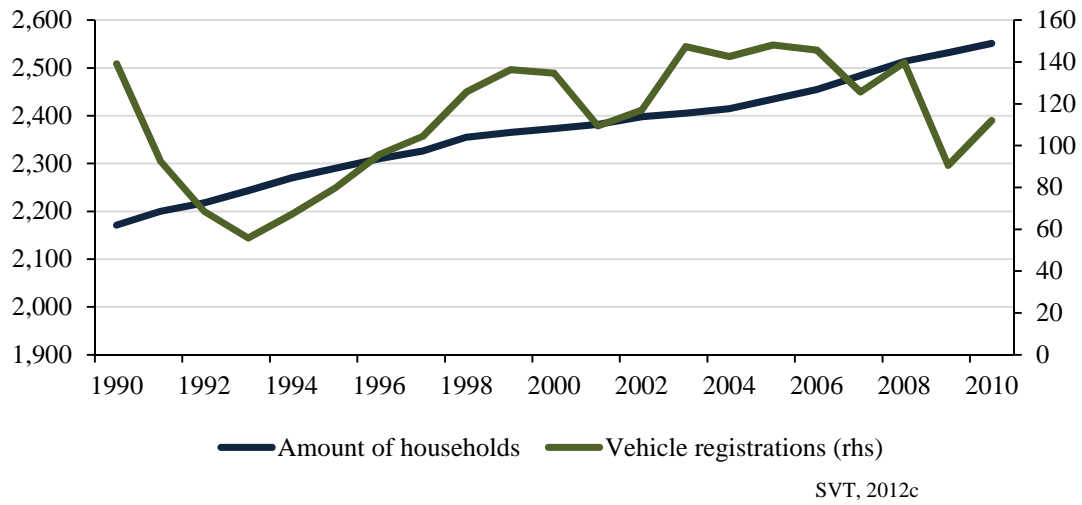


**Figure 6 Average vehicle prices and new vehicle registrations in Finland 2001-2010 (ICCT 2011)**

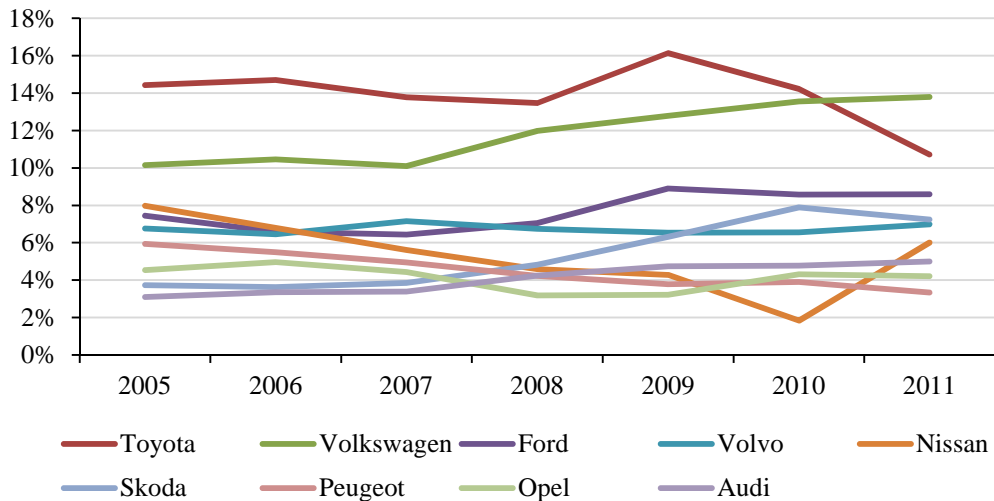




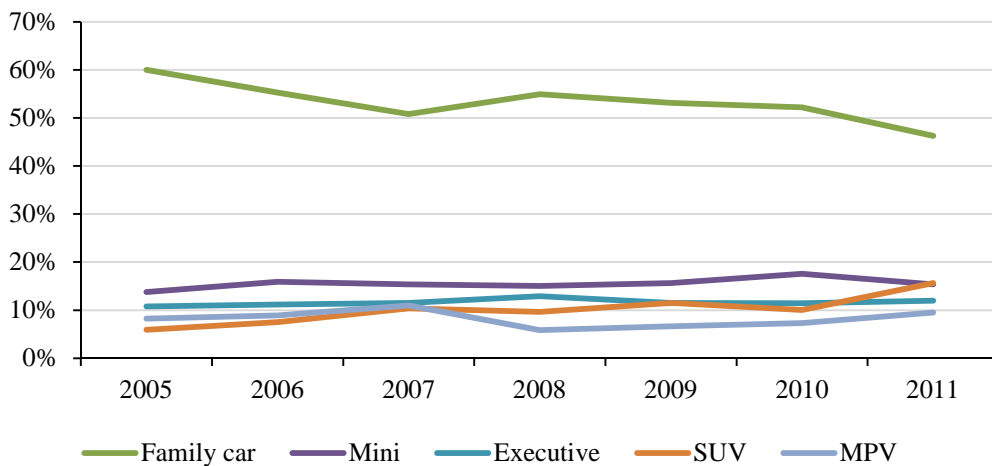
**Figure 7 Vehicle registrations ('000) and the amount of households in Finland ('000) (SVT, 2012c and Trafi, 2012)**



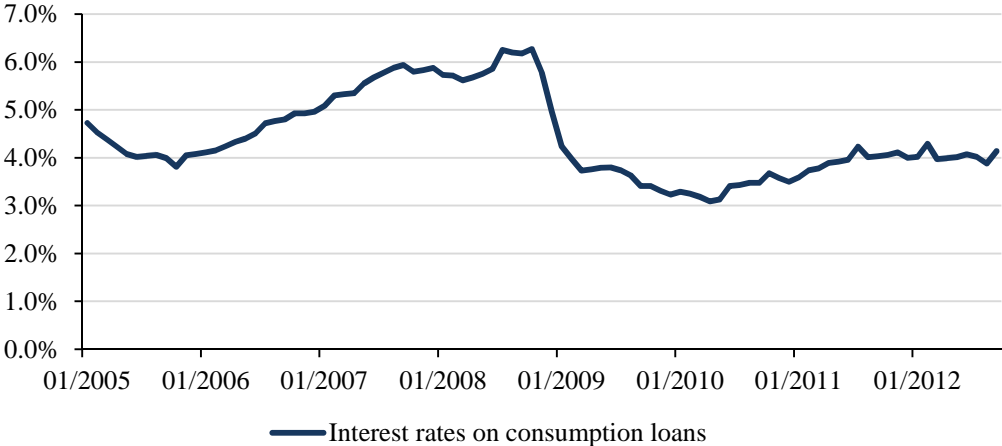
**Figure 8 The evolution in the market share of the most popular makes 2005-2011**



**Figure 9 The evolution in the market share of different vehicle types 2005-2011**



**Figure 10** The average interest rates on consumption loans in Finland (Suomen Pankki, 2012)



## Tables

**Table 1 The amount of vehicles registered by make and year**

<b>Make</b>	<b>2005</b>	<b>2006</b>	<b>2007</b>	<b>2008</b>	<b>2009</b>	<b>2010</b>	<b>2011</b>	<b>Grand Total</b>
TOYOTA	21,202	21,136	16,929	18,535	14,360	15,101	13,325	120,588
VOLKSWAGEN	14,901	15,022	12,413	16,485	11,378	14,398	17,155	101,752
FORD	10,936	9,459	7,906	9,714	7,918	9,108	10,688	65,729
VOLVO	9,930	9,280	8,788	9,291	5,811	6,959	8,691	58,750
NISSAN	11,727	9,755	6,889	6,325	3,808	1,952	7,477	47,933
SKODA	5,475	5,216	4,723	6,641	5,619	8,369	9,013	45,056
PEUGEOT	8,739	7,905	6,073	5,829	3,370	4,135	4,154	40,205
OPEL	6,671	7,132	5,451	4,387	2,870	4,578	5,246	36,335
AUDI	4,562	4,815	4,153	5,832	4,215	5,076	6,219	34,872
KIA	3,614	5,803	5,347	6,720	2,545	4,218	6,129	34,376
HONDA	4,669	5,641	6,571	6,255	4,039	3,297	3,292	33,764
CITROEN	6,685	5,440	5,678	5,426	2,219	3,484	3,567	32,499
MERCEDES-BENZ	4,162	4,069	3,652	4,714	3,719	4,459	4,973	29,748
MAZDA	4,423	4,917	4,391	4,909	2,618	2,720	2,119	26,097
BMW	2,656	2,395	2,320	4,355	2,794	3,158	4,001	21,679
HYUNDAI	2,637	2,915	2,833	3,070	2,058	2,900	4,466	20,879
RENAULT	6,972	4,408	1,913	2,076	1,281	1,749	1,872	20,271
FIAT	4,982	4,318	3,045	3,808	1,278	1,674	1,085	20,190
SEAT	1,311	2,247	2,503	3,192	1,425	2,269	2,945	15,892
CHEVROLET	2,194	1,618	1,751	849	726	1,119	1,425	9,682
MITSUBISHI	1,161	1,407	1,264	1,599	819	922	1,498	8,670
SAAB	1,322	1,801	1,588	1,286	400	203	452	7,052
CHRYSLER	1,691	1,783	1,450	695	252	173	14	6,058
SUZUKI	662	1,010	1,051	1,069	664	593	772	5,821
SUBARU	1,226	521	537	682	329	1,065	741	5,101
SMART	355	935	369	542	553	664	831	4,249
DODGE		521	1,096	1,184	861	423	34	4,119
ALFA ROMEO	369	417	292	269	97	265	491	2,200
JEEP	204	372	556	437	171	106	89	1,935
LAND ROVER	407	361	419	309	81	130	165	1,872
LADA	455	513	229	216	116	4	1	1,534
MINI	163	129	147	335	227	212	258	1,471
JAGUAR	271	150	264	311	135	113	113	1,357
DACIA					31	379	836	1,246
LEXUS	116	221	162	210	118	129	217	1,173
PORCHE	57	32	58	33	38	55	94	367
CADILLAC	43	30	20	7	6	2		108
LANCIA			11	33	33	15		92
FERRARI			2	7		1	2	12
BENTLEY	3	5	2	1	1			12
MASERATI	1	3	4	2		2		12
LAMBORGHINI	2	1		1				4
HUMMER				2				2
<b>Grand Total</b>	<b>146,956</b>	<b>143,703</b>	<b>122,850</b>	<b>137,643</b>	<b>88,983</b>	<b>106,179</b>	<b>124,450</b>	<b>870,764</b>

**Table 2 The results from regressing real price on price instruments**

	<b>Coef.</b>	<b>SE</b>	<b>t</b>	<b>P&gt; t </b>
ins_fuel3	-279.922	49.834	-5.62	0.000
ins_mass3	-2.429	0.268	-9.07	0.000
ins_power3	18.231	1.987	9.18	0.000
ins_seat3	215.517	73.741	2.92	0.004
ins_lenght3	0.477	0.109	4.38	0.000
ins_fuel1	-14,230	323	-44.03	0.000
ins_power1	11.217	1.506	7.45	0.000
ins_lenght1	-0.175	0.060	-2.91	0.004
_cons	229,000,000	5,190,530	44.04	0.000
<b>F( 8, 1825)</b>	=	538.39		
<b>Prob &gt; F</b>	=	0.0000		
<b>R-squared</b>	=	0.7024		
<b>Adj R-squared</b>	=	0.7011		

**Table 3 Correlation matrix for vehicle characteristics in the dataset**

	<b>Price</b>	<b>Fuel cons.</b>	<b>Length</b>	<b>Seats</b>	<b>Power</b>	<b>Doors</b>	<b>Mass</b>
<b>Price</b>	1,0000						
<b>Fuel cons.</b>	0,7988	1,0000					
<b>Length</b>	0,4138	0,5509	1,0000				
<b>Seats</b>	-0,2078	-0,0431	0,3510	1,0000			
<b>Power</b>	0,8991	0,8656	0,5028	-0,1967	1,0000		
<b>Doors</b>	-0,3033	-0,2164	0,1346	0,5482	-0,2994	1,0000	
<b>Mass</b>	0,5030	0,6752	0,8151	0,3306	0,5806	0,1051	1,0000

**Table 4 Summary of variables**

<b>Variable</b>	<b>Obs</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>
year	2807	2008	2	2005	2011
amount	1982	439	881	0	9328
marketshare	1982	0.353%	0.698%	0.000%	6.347%
nestshare	1879	8.834%	15.787%	0.003%	100.000%
realprice	1968	49,093	48,432	8,873	452,668
literper100m	1937	8.29	2.53	0.00	21.10
eurper100km	1937	11.24	3.40	0.00	30.56
lifetimetotal	1937	60,586	28,121	0	185,605
power	1924	129	72	0	458
mass	1925	1585	366	730	2689

**Table 5 Nests and amounts of make-model combinations belonging to a nest**

Vehicle class	Amount	%-share
Small Family Car	51	12.72%
Supermini	41	10.22%
Sports Car	30	7.48%
Large Family Car	29	7.23%
Compact Crossover SUV	27	6.73%
Executive Car	25	6.23%
Van	25	6.23%
City Car	21	5.24%
Compact MPV	21	5.24%
Large MPV	19	4.74%
Compact Executive car	18	4.49%
Large 4X4	17	4.24%
Mid-size Crossover SUV	15	3.74%
Mini MPV	14	3.49%
Compact 4x4	9	2.24%
Leisure Activity Vehicle	8	2.00%
Luxury Car	8	2.00%
Grand Tourer	6	1.50%
Mini 4x4	6	1.50%
Convertible	5	1.25%
Pick-up	3	0.75%
Full-size Crossover SUV	2	0.50%
Minibus	1	0.25%
<b>Total</b>	<b>401</b>	<b>100.00%</b>

**Table 6 Results from our baseline IV regression**

Dependent variable: lnms, Instrumented variable: realprice

	Coef.	Std. Err.	z	P> z
realprice	-0.0000383	0.0000107	-3.56	0.000
lifetimetotal	0.0000082	0.0000029	2.88	0.004
lnns	0.9450705	0.0106449	88.78	0.000
y6	0.0467168	0.0365105	1.28	0.201
y7	0.0258058	0.0421100	0.61	0.540
y8	-0.1212139	0.0546103	-2.22	0.026
y9	-0.1456088	0.0476007	-3.06	0.002
y10	-0.1873895	0.0663895	-2.82	0.005
y11	-0.2132358	0.0902950	-2.36	0.018
_cons	-2.3344010	0.4101530	-5.69	0.000
<b>Number of obs</b>	1749			
<b>Number of groups</b>	376			
<b>R-sq within</b>	0.8613			
<b>R-sq between</b>	0.465			
<b>R-sq overall</b>	0.5033			
<b>sigma_u</b>	1.835			
<b>sigma_e</b>	0.357			
<b>rho</b>	0.964			
<b>F test that all u_i=0:</b>	72.74			
<b>Prob &gt; F</b>	0.000			

**Table 7 Estimation results from different specifications**

	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>
<b>Real price</b>	-0.0000383	-0.0000459	-0.0000577	-0.0000786	-0.0000495	-0.0000484	-0.0000365
s.e.	(0.0000107)	(0.0000282)	(0.000014)	(0.0000348)	(0.0000154)	(0.0000106)	(0.00000952)
<b>Lifetime fuel costs</b>	0.0000082	-0.00000996	0.00000555	-0.0000146	0.00000123	0.0000114	0.000013
s.e.	(0.00000285)	(0.00000746)	(0.00000238)	(0.00000595)	(0.00000155)	(0.00000277)	(0.00000416)
<b>Log of nest share</b>	0.9450705		0.9347322		0.9463502	0.9596029	0.9470003
s.e.	(0.0106449)		0.0117		0.0088823	0.0107249	(0.0105251)
<b>Power</b>			0.0133357	0.0238291			
s.e.			(0.0033941)	(0.008388)			
<b>Mass</b>			0.0012082	0.0013163			
s.e.			(0.0002729)	(0.0006789)			
$\gamma / \alpha$	<b>-0.2141</b>	<b>0.2170</b>	<b>-0.0962</b>	<b>0.1858</b>	<b>-0.2485</b>	<b>-0.2355</b>	<b>-0.3562</b>

\* All specifications include time dummies for 2006-2011.

<b>1</b> Baseline model: nested logit, endogenous price	<b>5</b> Price not instrumented
<b>2</b> Multinomial logit	<b>6</b> Less detailed nests
<b>3</b> Baseline, power and mass included	<b>7</b> Same assumptions for all vehicles in lifetime fuel cost
<b>4</b> Multinomial logit, power and mass included	

## Appendix A

Constructing a random utility discrete choice model begins with adding a random component  $\varepsilon$  to a ‘conventional’ deterministic component  $V$  of a utility function:

$$U = V(s, x) + \varepsilon(s, x)$$

The component  $\varepsilon$  thus captures the part which the individual knows with certainty and affects his/her choice, but which the econometrist cannot observe.  $V$  on the other hand refers to the ‘representative’, or deterministic part of the utility function. The term  $x$  represents an alternative belonging to a universe of objects of choice  $X$ , and the term  $s$  represents the characteristics of the consumer affecting his/her utility.

How do we then use this utility specification to construct a model of consumer choices? McFadden (1974) considers a consumer facing an alternative set  $B$  with  $J$  alternatives indexed  $j = 1, \dots, J$  choosing a particular alternative, given his/her characteristics  $s$ . He then assumes the consumer to have a so-called behavioral rule function  $h$  which, given a set of attributes  $s$  and an alternative set  $B$  maps into the member  $x$  of  $B$  that is chosen.

$$h(s, B) = x$$

The econometrist cannot observe the behavioral rule of each consumer, but knows the distribution of  $h$ 's belonging to the behavioral rule set  $H$ . There exists a probability  $\pi$  for each outcome given the distribution. Thus a consumer's choice is not deterministic due to a stochastic behavioral rule. Now we can model this multinomial choice situation (i.e. the consumer faces more than 2 alternatives) in terms of the probability  $P$  that some consumer randomly drawn from the population, given the distribution of behavioral rule functions, chooses the alternative  $x$ :

$$P(x|s, B) = \pi[\{h \in H | h(s, B) = x\}]$$

Now a consumer chooses the alternative that maximizes his/her utility. Thus the probability  $P_i$  that a randomly drawn consumer chooses the alternative  $x_i$  is equal to

$$P_i = \pi[\{h \in H | h(s, B) = x_i\}] = P[U_i > U_j] = P[\varepsilon(s, x_i) - \varepsilon(s, x_j) < V(s, x_i) - V(s, x_j)]$$

for all  $j \neq i$

Now since  $\varepsilon(s, x_j)$  is a stochastic component, let's assume a joint cumulative distribution function  $F(\varepsilon_1, \dots, \varepsilon_J)$ , where  $\varepsilon_j = \varepsilon(s, x_j)$ , which induces the probability  $\pi$  given in the above expression:

$$F(\varepsilon_1, \dots, \varepsilon_J) = \pi[\{h \in H | \varepsilon(s, x_j) \leq \varepsilon_j \text{ for all } j = 1, \dots, J\}]$$

Thus  $F(\varepsilon_1, \dots, \varepsilon_J)$  defines the joint probability that the stochastic utility components  $\varepsilon$  for each alternative  $x_j$  are below  $\varepsilon$  some value  $\varepsilon_j$ . To define  $P_i$ , we need to define the joint probability that the stochastic component  $\varepsilon$  of each of the alternatives  $j$  complies with the condition that the alternative  $x_i$  is utility-maximizing. Now the condition for  $x_i$  being utility-maximizing can be rewritten as

$$\varepsilon(s, x_j) < \varepsilon(s, x_i) + V(s, x_i) - V(s, x_j) \text{ for all } j \neq i.$$

To simplify the notation, let's denote  $V(s, x_i) = V_i$  and  $V(s, x_j) = V_j$  etc. We then have

$$\begin{aligned} & F(\varepsilon(s, x_i) + V_i - V_1, \dots, \varepsilon(s, x_i) + V_i - V_J) \\ &= \pi[\{h \in H | \varepsilon(s, x_j) \leq \varepsilon(s, x_i) + V_i - V_j \text{ for all } j = 1, \dots, J\}], \end{aligned}$$

which is the joint cumulative distribution of the  $\varepsilon_j$ 's evaluated at  $\varepsilon(s, x_i) + V_i - V_j$ . Of course  $\varepsilon(s, x_i)$  can take many values, and this fact has to be taken into account when constructing the expression for the choice probability of  $x_i$ . Let  $F_i$  denote the partial derivative of  $F$  with respect to its  $i$ th argument. It is thus the density function describing how  $\varepsilon(s, x_i)$  is distributed across consumers depending on the distribution of the behavioral rule  $h$ .  $F_i(\varepsilon + V_i - V_1, \dots, \varepsilon + V_i - V_J)$  tells us then the probability of the occurrence of some value  $\varepsilon$  of  $\varepsilon(s, x_i)$  given that  $x_i$  maximizes utility. Since the  $\varepsilon(s, x_i)$  is not given, we now write the probability  $P_i$  of a random consumer choosing  $x_i$  by summing the above mentioned probabilities over all the values of :

$$P_i = \int_{\varepsilon=-\infty}^{\infty} F_i(\varepsilon + V_i - V_1, \dots, \varepsilon + V_i - V_J) d\varepsilon.$$



We thus have an expression for  $P_i$  which depends among other things on the shape of the joint cumulative distribution.

## Appendix B

Luce (1959) and McFadden (1974) derive the logit probabilities based on the IIA assumption. An alternative approach, adopted by Train (2003), is to derive the logit probabilities from the assumption that the stochastic components  $\varepsilon$  are independently and identically distributed type I extreme value. In fact, McFadden (1974) shows that if the choice probabilities are assumed to follow the logit formula, it necessarily implies that  $\varepsilon$  is distributed extreme value. The main implication of this distribution is that the individual terms  $\varepsilon$  belonging to each alternative are independent of each other, and thus similarly to the IIA assumption, does not take into account the possible existence of substitutes among alternatives. Train (2003) expresses the cumulative distribution function for each of the stochastic utility component as

$$F(\varepsilon_j) = e^{-e^{-\varepsilon_j}}$$

and the density function as

$$f(\varepsilon_j) = e^{-\varepsilon_j} e^{-e^{-\varepsilon_j}}$$

and uses them to derive the probability  $P_i$ . The fact that the  $\varepsilon$ 's are distributed independent allows us to rewrite the expression for the joint cumulative distribution as

$$F(\varepsilon_1, \dots, \varepsilon_j) = \prod_{j \neq i} e^{-e^{-\varepsilon(s, x_j)}} (e^{-e^{-\varepsilon(s, x_i)}}),$$

since the joint cumulative distribution is simply the product of the individual cumulative distributions over all  $j$ . Since  $\varepsilon(s, x_i)$  is unknown, we have to sum the product over all the possible values of  $\varepsilon(s, x_i)$ . We do this by taking the derivative of  $F(\cdot)$  with respect to  $\varepsilon(s, x_i)$ :

$$F_i(\varepsilon_1, \dots, \varepsilon_J) = \prod_{j \neq i} e^{-e^{-\varepsilon(s, x_j)}} (e^{-\varepsilon_i} e^{-e^{-\varepsilon(s, x_i)}})$$

and sum it over all the values of  $\varepsilon(s, x_i)$  at point  $\varepsilon_1, \dots, \varepsilon_J = \varepsilon(s, x_i) + V_i - V_1, \dots, \varepsilon(s, x_i) + V_i - V_J$  such that the utility maximization condition holds:

$$\int_{-\infty}^{\infty} \prod_{j \neq i} e^{-e^{-(\varepsilon + V_i - V_j)}} (e^{-\varepsilon} e^{-e^{-\varepsilon}}) d\varepsilon = P_i$$

We can then rewrite this function for the choice probability as:

$$P_i = \frac{e^{V_i}}{\sum_j e^{V_j}}$$

The manipulation of the expression for P to the latter form can be found in Train (2003). We thus acquire a quite simple logit formula for the choice probabilities.