Automobile Replacement: a Dynamic Structural Approach

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Abstract

This paper specifies and estimates a structural dynamic model of consumer preferences for new and used durable goods. Its primary contribution is to provide an explicit estimation procedure for transaction costs, which are crucial to capturing the dynamic nature of consumer decisions. In particular, transaction costs play a key role in determining consumer replacement behavior in both primary and secondary markets for durable goods. The data set used in this paper is collected by the Italian Motor Registry and covers the period from 1994 to 2004. It includes information about sales dates for individual cars over time as well as the initial stock of cars in the sample period. Identification of transaction costs is achieved from the variation in the share of consumers choosing to hold a given car type each period, and from the share of consumers choosing to purchase the same car type that period. Specifically, I estimate a random coefficients discrete choice model that incorporates a dynamic optimal stopping problem in the spirit of Rust. I conclude by applying this model to evaluate the impact of scrappage subsidies on the Italian automobile market in 1997 and 1998.

1 Introduction

In many durable good industries, such as automobiles, used products are often traded in decentralized secondary markets. The U.S. Department of Transportation reports that in

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2004 13.6 million new vehicles and 42.5 million used vehicles were sold in the U.S.A; in the same year 2.5 million new vehicles and 4.7 million used vehicles were sold in Italy. Transactions in the secondary market may occur because the quality of a durable deteriorates over time and current owners sell their product in order to update to their preferred quality. Alternatively the level of required maintenance and/or the probability of failure may increase as the automobile ages making replacement of the current unit desirable.

Durability and the presence of second-hand markets introduce dynamic considerations into both producers' output decisions and consumers' purchase decisions in the automobile market. Empirical models of demand for durable goods have mostly focused on the market for new products (Berry, Levinshon and Pakes (1995) —henceforth BLP, Bresnahan (1981)). Using sophisticated simulation techniques embodied in the logit framework, these models are able to allow for general patterns of substitution across differentiated products. However, they do not usually account for the intertemporal dependence of consumers' decisions that characterize markets for durable goods. They either ignore the secondary market and its dynamics altogether or lump used goods into a composite outside option. In spite of their importance, there have been relatively few empirical models of secondary markets for used goods. Notable exceptions are Esteban and Shum (2006), Stolyarov (2002).

An important feature of the automobile market is that the stock of cars held by consumers is persistent over time. If a consumer owns a car in one year then it is likely that she will hold the same car the following year as well. The persistence of consumer holdings of automobiles arises because of unobserved consumer heterogeneity constant over time and the presence of transaction costs such as searching costs, taxes, asymmetric information, switching costs, etc. Transaction costs, essential factors that drive consumer holdings of durable goods are unobservable and vary over time. They tend to make replacement infrequent because consumers try to economize on these costs.

Any model that tries to explain the pattern of consumer holdings in a market for semi-durable goods must explicitly account for dynamic consumer considerations and the cost of the replacement decision. The model that I present incorporates both of these features as well as consumers' uncertainty about future product characteristics and prices. Without transaction costs there is an undesirable feature seen in some models, where consumers trade durables every period and the persistence in the stock is difficult to explain. Information about resales along with ownership data of used cars provides a potential source of identification for the transaction costs which has not been fully explored in previous literature. I use a data set containing information about the Italian car market to examine how unobserved heterogeneity and transaction costs affect replacement behavior. In particular, I observe the pattern of sales and ownerships for each individual car type in the sample over a period of 11 years. The possibility of following the history of each vehicle in the sample is due to the presence, in the data, of a unique identification number assigned to each unit. The data are from the Province of Isernia in Italy and are collected by the Motor Vehicle Department. I observe a significant inflow and outflow of vehicles over time. These features of the data lead me to focus only on demand estimation rather than to consider a general equilibrium approach in the secondary market where the price is endogenously computed by equating supply and demand. Identification of transaction costs is achieved from the difference between the share of consumers choosing to hold a given car type each period, and the share of consumers choosing to purchase the same car type that period. These market shares are the results of the consumers' optimal decision that takes into account for the depreciation of automobiles over time. This depreciation is captured in the data by the decline in prices; then the pattern of sales and holdings along with the pattern of prices is used to identify the transaction costs. The structural model explicitly accounts for this information and provides a nonparametric estimation of these costs for each product at each point in time.

Finally, I investigate the effect of scrappage subsidies offered by the Italian government to stimulate the early voluntary removal of used cars in 1997 and 1998. Such subsidies were temporary and offered in exchange for used cars of delineated vintages to reduce environmental pollution and stimulate car sales. Scrappage subsidies have been very popular in the European Union as well as in the United States and Canada. The possibility that such programs will be expanded has evoked a debate surrounding their effects on car markets and consumers welfare. The model is used to investigate the impact of such policies on consumers' demand for new and used vehicles.

The contribution of this paper to the durable goods literature is twofold. First, it is the first paper which studies replacement behavior in the presence of secondary markets using aggregate data while allowing for heterogeneity across consumers and endogeneity of price in a dynamic setting. Second, it shows how the combination of ownership and purchase data is useful to infer the size of transaction costs.

I estimate a discrete logit choice model over a set of products with random coefficients on observable product characteristics that incorporates a dynamic optimal stopping problem in the spirit of Rust (1987) using market-level data. The random coefficients allow us to relax the so-called independence of irrelevant alternative (IIA) property (see BLP (1995), Browstone and Train (1999)) and allows the error preferences to be correlated across vehicles. Thus I construct a generalized method of moments (GMM) estimator to deal with potential price endogeneity, and this is possible provided that one can recover the unobserved product characteristics. The moment conditions are constructed from the orthogonality between unobserved product characteristics and exogenous variables (Berry 1994). An important contribution of the present paper is the estimation strategy for the transaction costs. Berry (1994) suggests the use of a contraction mapping to find the mean product characteristics.

I use a similar contraction mapping to invert the market share of purchases and the market share of consumer holdings for each product. Both market shares for each car type deliver information about the mean level utility and the mean level of transaction costs. As suggested by the theory, in a model where transaction costs are paid by buyers, the market share of consumer holdings depends on the mean product characteristics, whereas the market share of purchases will, in addition, depend on transaction costs. For each product, I solve for the vectors of mean product characteristics and transaction costs that make the predicted shares match the observable ones. Because no individual data is available, I need to compute the aggregate predicted share of each product at any time period. Doing so requires integrating over the individual heterogeneity and consumer holdings once she decides to replace her current vehicle. Then, I allow consumers to solve dynamic optimization problem based on expectations about the stochastic process that governs the transition across different states of the durables and the market evolution. As in Rust (1987), the consumer's decision problem is formulated as an optimal stopping problem. Therefore, the consumer decides the optimal time period in which to replace her current vehicle with a different one or to exit the market altogether. In my analysis the consumer's decision to replace a car depends on her expectation about the future value of the product she currently owns and on the perceived distribution about the future set of products available. The uncertainty in these expectations creates an inherent trade-off. If consumers expect little changes in product utility, they are more likely to hold the durable to economize on transaction costs. When the durable good depreciates more, they are more likely to replace their car.

The emphasis on the consumers' dynamic decisions due to the depreciation of the durables and the secondary market with transaction costs distinguishes the present model from BLP and Gowrisankaran and Rysman (2006). Gowrisankaran and Rysman (2006) extended Melnikov's (2001) model to include consumer heterogeneity and examine the pattern of sales after the introduction of new digital cameras and DVD players. As in those models the major simplifying assumption here is that consumers perceive the evolution of product characteristics to be a simple first order Markov process, where the distribution of next period's product characteristics is a polynomial function of a simple statistic: the logit inclusive value (Melnikov, 2001). Gordon (2006) allows consumers to have the possibility of replacing the good, but that model does not allow for price endogeneity and heterogeneity across consumers.

There are recent studies that deal with the implications of durability and secondary markets on the dynamics of car demand. Esteban and Shum (2006) estimate a model with forward-looking consumers and firms. However, they restrict consumer heterogeneity to a single dimension, and do not consider the presence of transaction costs. Having a single dimension and considering vertically differentiated market places strong restrictions on the substitutability among cars in consumers' choice sets. Durables sold in second-hand markets are typically highly differentiated in quality and this captures some of the motivations for consumer holdings. Stolyarov (2002) uses a dynamic model with transaction costs to replicate the pattern of resales in the used car market. His model restricts consumer heterogeneity to a single dimension, but does allow for the possibility of infrequent replacement. However, he looks at a stationary environment in which all the goods are homogenous in all aspects but the age. Transaction costs increase deterministically over time. The model is calibrated to match the cross sectional pattern of resales. It does not allow transaction costs to be different across different cars and across time. Adda and Cooper (2000) study the optimal decision rules from a dynamic discrete-choice model to explore the effects of scrappage subsidies on new car demand in France. However, in their model consumers are homogenous so that in equilibrium agents will choose either to keep the car or to replace it with a new one by scrapping their old car. Hence, in their model, in equilibrium there is no active secondary market. Finally, Hendel and Lizzeri (1999) and Porter and Sattler (1999) study a setting in which durable goods live for just two periods, so that used goods of all age are lumped together. Clearly, those models are not able to capture the complexity of the resale pattern in the secondary market.

The reminder of this paper is organized as follows. Section 2 discusses the model and the method of inference. Section 3 analyses the data. Section 4 presents the results. Section 5 investigates the effect of scrappage subsidies on the Italian automobile. Section 6 concludes.

2 Model and Inference

There are T periods and finite types of durable goods (BMW, Mercedes, FIAT, and so on). Each good lies in one of a variety of different states according to a summary statistic that maps its multidimensional characteristics (e.g., vintage, engine displacement, brand, price) to a single-dimensional index as explained below. The good is durable, but it depreciates over time. A physical stochastic process describes the transformation of the condition of the vehicle in period t to its condition in period $t+1$.

Each consumer is assumed to consume at most one unit of the good. Since products degrade over time, a given consumer will occasionally desire to replace her durable, either with a brand new durable or with a secondhand one. In the model, consumers have perfect information about durables so that there is no lemon problem. In addition there is a perfectly divisible good (money), which is treated as numeraire. Consumers maximize the expected lifetime utility using a discount factor $\beta < 1$.

At the beginning of each period, each consumer i may or may not have a previously bought car. If she does not have any vehicle, she simply decides whether or not to purchase one. If she has a car endowment $\widetilde{k}$, immediately upon entering period t the durable depreciates according to the exogenous depreciation process to a new state. Then the consumer decides whether to hold, sell or scrap that car. If she gets rid of the car (via scrap or sale), she also decides whether or not to purchase a different car among the J_t products present in the primary or secondary market in period t. In either case, she faces a similar (though not identical) decision problem in time $t+1$. The consumer's choice maximizes her expected discounted utility conditional on her information and endowment in that period.

Each product j in period t is characterized by observed physical characteristics x_{jt} , the price p_{jt}, the unobserved (by the econometrician) product characteristic ξ_{jt} and the unobserved (by the econometrician) transaction cost τ_{jt}. I assume that the transaction cost is paid by the consumer every time that she purchases a car and it captures the presence of searching costs, financial costs, switching costs, asymmetric information and so on. A consumer who has no product obtains some base flow utility that is normalized to zero. Moreover, assume that even if two products in subsequent years have the same make and model and the same observable characteristics x_{jt} and x_{jt+1}, they can differ on their unobservable characteristics ξ_{jt} and ξ_{jt+1}.

I assume that a consumer purchasing product j at time t receives a net utility flow of

$$u_{ijt} = x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p p_{jt} - \tau_{jt} + \epsilon_{ijt} \tag{1}$$

where p_{jt} is the price of product j in period t, x_{jt} is the K-dimensional vector of observed characteristics of product j (for example engine displacement, fuel, age, size, etc.), ξ_{jt} is the unobserved product characteristic, τ_{jt} is the unobservable transaction cost associated with a purchase of a durable and ϵ_{ijt} is the mean-zero stochastic term. Assume that the error term is independent across consumers, products and time and is Type I extreme value distributed. Finally α_i^p is the consumer $i's$ marginal utility from income and α_i^x is a K-dimensional vector of individual-specific taste coefficient. Notice that the preference parameters vary across consumers, so that $\alpha_i^p = \alpha^p + \sigma_{\alpha^p} \upsilon_{i\alpha^p}$ and $\alpha_{ik}^x = \alpha_k^x + \sigma_{\alpha_k^x} \upsilon_{i\alpha_k^x}$ where $\upsilon_{i.}$ is drawn from a *iid* distribution $P_\upsilon(\upsilon)$. The flow utility of a consumer who owns a good $\widetilde{k}$ is:

$$\begin{cases} \widetilde{u}_{i\widetilde{k}t} = x_{\widetilde{k}t}\,\alpha_i^x + \xi_{\widetilde{k}t} + \epsilon_{i\widetilde{k}t} & \text{if } \widetilde{k} \neq 0 \\ \widetilde{u}_{i\widetilde{k}t} = 0 & \text{if } \widetilde{k} = 0 \end{cases}$$

In formulating the problem, I assume that the age of the automobile and the unobserved product characteristic are the elements that capture the depreciation of durables over time. The depreciation is not deterministic because of the presence of the unobserved product characteristic that evolves stochastically over time. Given this assumptions we can interpret $\widetilde{u}_{\widetilde{k}t}$ as the mean current utility derived from having an automobile of age x so that p_{jt} is the price paid to buy a used product j of that age in period t.[1]

[1]As explained ahead in the paper, this feature is further relaxed because of the presence of random coefficients when I formally define the state of the durable.

In order to evaluate consumer i's choice at time t, I need to formalize consumer i's expectations about the utility from future products and from the product that she potentially owns. I assume that consumers have no information about the future values of the idiosyncratic unobservable shocks ϵ_{ijt} beyond their distribution. The set of products, their prices and characteristics and transaction costs vary across time, due to entry and exit, technological progress and changes in prices for existing products according to optimal price decisions. Consumers are uncertain about the future product attributes, but rationally expect them to evolve based on the current market structure. Then, the purchase/replacement decision for consumer i depends on the following: her coefficients α_i, her utility flow of the good that she currently owns, her idiosyncratic unobservable draws ϵ_{ijt}, and the current and future realizations of product attributes including transaction costs.

Let Ω_t represent all the information available to consumers in period t. It includes information about future characteristics and future prices as a function of the current market environment. I group all this information together and I assume that Ω_t evolves according to some Markov process $P\left(\Omega_{t+1}|\Omega_t\right)$. Let $\epsilon_{i.t} \equiv (\epsilon_{i1t}, ..., \epsilon_{iJ_tt})$ denote the set of idiosyncratic utility components for consumer i at period t. Then, the purchase decision for consumer i depends on $\epsilon_{i.t}$, Ω_t and her endowment $\widetilde{k}$.[2]

Based on her post-depreciation endowment durable $\widetilde{k}$, the consumer decides whether to replace $\widetilde{k}$ and determines an optimal replacement $j \in J_t \cup \{0\}$. Define the consumer's value function V_i such that:

Case-1: $\widetilde{k} \neq 0$

$$V_i\left(\epsilon_{i.t}, \widetilde{k}, \Omega_t\right) = \max \left\{ \begin{array}{c} \widetilde{u}_{i\widetilde{k}t} + \beta E\left[V_i\left(\epsilon_{i.t+1}, \widetilde{k}', \Omega_{t+1}\right)|\Omega_t\right], \\ \max_{j\in\{1,\ldots,J_t\}}\left\{u_{ijt} + \alpha_i^p p_{\widetilde{k}t} + \beta E\left[V_i\left(\epsilon_{i.t+1}, j', \Omega_{t+1}\right)|\Omega_t\right]\right\} \\ \alpha_i^p p_{\widetilde{k}t} + \beta E\left[V_i\left(\epsilon_{i.t+1}, 0, \Omega_{t+1}\right)|\Omega_t\right] \end{array} \right\} \quad (2)$$

Case-2: $\widetilde{k} = 0$

$$V_i\left(\epsilon_{i.t}, 0, \Omega_t\right) = \max \left\{ \begin{array}{c} \beta E\left[V_i\left(\epsilon_{i.t+1}, 0, \Omega_{t+1}\right)|\Omega_t\right], \\ \max_{j\in\{1,\ldots,J_t\}}\left\{u_{ijt} + \beta E\left[V_i\left(\epsilon_{i.t+1}, j', \Omega_{t+1}\right)|\Omega_t\right]\right\} \end{array} \right\} \quad (3)$$

As suggested in Rust (1987) in order to deal with the dimensionality problem associated with the presence of the unobservable $\epsilon_{i.t}$, define the expectation of the value function integrated over the realizations of $\epsilon_{i.t}$ as:

[2] More specifically, the purchase decision depends on the characteristics associated with good $\widetilde{k}$.

$$\widehat{EV}_i(j,\Omega_t) = \int_{\epsilon_{i.t}} V_i(\epsilon_{i.t+1}, j', \Omega_{t+1})\, dP_\epsilon \quad (4)$$

so that $\widehat{EV}_i$ is no longer function of $\epsilon_{i.t}$ and the choice probabilities will not need to be integrated over the unknown function $\widehat{EV}_i$. This allows $\widehat{EV}_i$ to be computed as a fixed point of a separate contraction mapping on the reduced space $\left(\widetilde{k}, \Omega_t\right)$.

Using (4) it is possible to rewrite the previous problem as follows:

Case-1: $\widetilde{k} \neq 0$

$$\widehat{EV}_i\left(\widetilde{k},\Omega_t\right) - \alpha_i^p p_{\widetilde{k}t} = \log\left(\begin{array}{c} \exp\left(x_{\widetilde{k}t}\,\alpha_i^x + \xi_{\widetilde{k}t} - \alpha_i^p p_{\widetilde{k}t} + \beta E\left[\widehat{EV}_i\left(\widetilde{k}',\Omega_{t+1}\right)|\Omega_t\right]\right) + \\ \sum_{j\in\{1,2,\ldots,J_t\}} \exp\left(x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p p_{jt} - \tau_{jt} + \beta E\left[\widehat{EV}_i(j',\Omega_{t+1})|\Omega_t\right]\right) \\ + \exp\left(\beta E\left[\widehat{EV}_i(0,\Omega_{t+1})|\Omega_t\right]\right) \end{array}\right) \quad (5)$$

Case-2: $\widetilde{k} = 0$

$$\widehat{EV}_i(0,\Omega_t) = \log\left(\begin{array}{c} \exp\left(\beta E\left[\widehat{EV}_i(0,\Omega_{t+1})|\Omega_t\right]\right) + \\ \sum_{j\in\{1,2,\ldots,J_t\}} \exp\left(x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p p_{jt} - \tau_{jt} + \beta E\left[\widehat{EV}_i(j',\Omega_{t+1})|\Omega_t\right]\right) \end{array}\right) \quad (6)$$

The dynamic consumers' optimization problem potentially depends on the whole set of information available in period t. In particular, it depends on the characteristics, prices and transaction costs of all the products available in the past and the decisions of firms to introduce products over time. The main issue in the estimation procedure is the "curse of dimensionality" usually associated with these kinds of problems. To simplify the dynamic optimization problem and reduce the state space for computing the expectation of the value function, it is convenient to define

$$EV_i\left(\widetilde{k},\Omega_t\right) = \widehat{EV}_i\left(\widetilde{k},\Omega_t\right) - \alpha_i^p p_{\widetilde{k}t} \quad (7)$$

and

$$\phi_{i\widetilde{k}t} \equiv x_{\widetilde{k}t}\,\alpha_i^x + \xi_{\widetilde{k}t} - \alpha_i^p p_{\widetilde{k}t} + \alpha_i^p \beta E\left[p_{\widetilde{k}'t+1}|\Omega_t\right] \quad (8)$$

The net augmented flow utility, $\phi_{i\widetilde{k}t}$, is a summary statistic that specifies the location of the durable in a particular state; it includes both elements of consumer characteristics and elements of product characteristics. This statistic captures the net flow utility derived by the consumer i from keeping the durable augmented by the expected price that she can get if she decides to sell her good in the secondary market in the following period. Notice that the change of variable suggested in equation (7) allows me to reduce by two the state variables of the dynamic optimization problem avoid having to introduce the price as a third state variable.[3] Finally the inclusive value for consumer i at time t is:

$$\phi_{it} = \ln\left(\sum_{j\in\{1,2,\ldots,J_t\}} \exp\left(\phi_{ijt} - \tau_{jt} + \beta E\left[EV_i\left(\widetilde{k},\Omega_t\right)|\Omega_t\right]\right)\right) \tag{9}$$

The logit inclusive value, ϕ_{it}, and the net current augmented-gain from having good $\widetilde{k}$, $\phi_{i\widetilde{k}t}$, are sufficient statistics for the distribution of the maximum utility that an agent can achieve over time. In particular, ϕ_{it} captures the expected value of buying a product in period t and $\phi_{i\widetilde{k}t}$ captures the expected value of keeping the durable endowment for the next period. We can interpret the consumer's choice as a sequential decision in which she first decides whether or not to replace the current good based on the predictions of future values of her endowment, product characteristics, prices and transaction costs. Then, she decides her optimal choice of the products available in the market.

I assume that consumers possess rational expectations about the stochastic process governing the evolution of the future value ϕ_{it} and $\phi_{i\widetilde{k}t}$. In general these values could depend on the entire state space Ω_t, but in order to solve for the consumers' dynamic optimization problem assume that the processes are modeled independently as one-dimensional Markov process:

$$P_i\left(\phi_{it+1},\phi_{i\widetilde{k}t+1}|\Omega_t\right) = P_i\left(\phi_{it+1},\phi_{i\widetilde{k}t+1}|\phi_{it},\phi_{i\widetilde{k}t}\right) = P_i\left(\phi_{it+1}|\phi_{it}\right)P_i\left(\phi_{i\widetilde{k}t+1}|\phi_{i\widetilde{k}t}\right) \tag{10}$$

I allow the conditional density $P_i(.|.)$ to vary by type i, this reflects the idea that ϕ_{it+1} and $\phi_{i\widetilde{k}t+1}$ incorporate both elements of future products and characteristics of consumers of type i (see Gowrisankaran and Rysman (2006)). Assume that the Markov processes take the following linear functional form:

$$\phi_{it+1} = \rho_{1i} + \rho_{2i}\phi_{it} + \eta_{it} \tag{11}$$

$$\phi_{i\widetilde{k}t+1} = \gamma_{1i} + \gamma_{2i}\phi_{i\widetilde{k}t} + \mu_{it} \tag{12}$$

[3] Without the transformation proposed above it is still possible to define two summary statistics similar to those proposed above. In particular it is possible to define $\phi_{i\widetilde{k}t} \equiv \delta_{i\widetilde{k}t} - \alpha_i^p p_{\widetilde{k}t}$ and $\phi_{it} = \ln\left(\sum_{j\in\{1,2,\ldots,J_t\}}\exp\left(\phi_{ijt} - \tau_{jt} + \beta E\left[\widehat{EV}_i(.)\right]\right)\right)$. However, the Bellman equation still depends from the price associated with the endowed good so that one still has to deal with a three-dimensional state variable probem. For $\widetilde{k} \neq 0$ we would have
$\widehat{EV}_i\left(\phi_{it},\phi_{i\widetilde{k}t},p_{\widetilde{k}t}\right) = \alpha_i^p p_{\widetilde{k}t} + \ln(\exp(\phi_{it}) + \exp\left(\beta E\left[\widehat{EV}_i\left(\phi_{it+1},0\right)|\phi_{it}\right]\right) + \exp\phi_{i\widetilde{k}t} + \beta E\left[\widehat{EV}_i\left(\phi_{i\widetilde{k}t+1},\phi_{it+1},p_{\widetilde{k}'t+1}\right)|\phi_{it},\phi_{i\widetilde{k}t},p_{\widetilde{k}t}\right])$

where η_{it} and μ_{it} are standard-normally distributed. Notice that equation (12) allows individuals to end up in different states only if they have different random coefficients. This assumption is restrictive in the sense that does not allow two goods that share the same characteristics to depreciate in different ways over time. Therefore, the model does not accommodate the possibility that fairly new cars can be scrapped. However, given that in the formulation what really matters for a consumer is the augmented net flow utility derived from owning a particular car, the model provides a distribution of this value associated with different random draws.[4] This implies that the aggregate distribution of automobiles over ages is not the same as the aggregate distribution over states.

Using the definitions (7), (8), (9) and the assumption (10), I can rewrite the Bellman equations as:

Case-1: $\widetilde{k} \neq 0$

$$EV_i\left(\phi_{it}, \phi_{i\widetilde{k}t}\right) = \ln\begin{pmatrix} \exp(\phi_{it}) + \exp\left(\beta E\left[EV_i\left(0, \phi_{it+1}\right)|\phi_{it}\right]\right) + \\ + \exp\left(\phi_{i\widetilde{k}t} + \beta E\left[EV_i\left(\phi_{i\widetilde{k}t+1}, \phi_{it+1}\right)|\phi_{it}, \phi_{i\widetilde{k}t}\right]\right) \end{pmatrix} \tag{13}$$

Case-2: $\widetilde{k} = 0$

$$EV_i\left(0, \phi_{it}\right) = \ln\left(\exp(\phi_{it}) + \exp\left(\beta E\left[EV_i\left(0, \phi_{it+1}\right)|\phi_{it}\right]\right)\right) \tag{14}$$

The aggregate demand for a product is determined by the solution to the consumer's optimization problem. Specifically the probability that a consumer of type $\left(i, \widetilde{k}\right)$ purchases a good $j \in J_t \cup \{0\}$ is:

$$d_{jt}\left(i, \widetilde{k}\right) =$$

$$\frac{\exp\left(\phi_{ijt} - \tau_{jt} + \beta E\left[EV_i\left(\phi_{ijt+1}, \phi_{it+1}\right)|\phi_{it}, \phi_{ijt}\right]\right)}{\exp(\phi_{it}) + \exp\left(\beta E\left[EV_i\left(0, \phi_{it+1}\right)|\phi_{it}\right]\right) + \exp\left(\phi_{i\widetilde{k}t} + \beta E\left[EV_i\left(\phi_{i\widetilde{k}t+1}, \phi_{it+1}\right)|\phi_{it}, \phi_{i\widetilde{k}t}\right]\right)} \tag{15}$$

Let $\widetilde{d}_{\widetilde{k}t}\left(i, \widetilde{k}\right)$ denote the probability that consumers of type $\left(i, \widetilde{k}\right)$ choose not to make a purchase and retain their existing product:

$$\widetilde{d}_{\widetilde{k}t}\left(i, \widetilde{k}\right) =$$

$$\frac{\exp(\phi_{i\widetilde{k}t} + \beta E\left[EV_i\left(\phi_{i\widetilde{k}t+1}, \phi_{it+1}\right)|\phi_{it}, \phi_{i\widetilde{k}t}\right])}{\exp(\phi_{it}) + \exp\left(\beta E\left[EV_i\left(0, \phi_{it+1}\right)|\phi_{it}\right]\right) + \exp\left(\phi_{i\widetilde{k}t} + \beta E\left[EV_i\left(\phi_{i\widetilde{k}t+1}, \phi_{it+1}\right)|\phi_{it}, \phi_{i\widetilde{k}t}\right]\right)} \tag{16}$$

[4] The random coefficients attached to the characteristics of the cars make the transition (from one state to the other) different for consumers that own the same product but have different preferences.

Integrating $d_{jt}\left(i,\widetilde{k}\right)$ and $\widetilde{d}_{\widetilde{k}t}\left(i,\widetilde{k}\right)$ over consumer preferences and summing $d_{jt}\left(i,\widetilde{k}\right)$ over all existing products I compute the market share of each product purchased and the market share for consumer holdings:

$$s_{jt}^{D} = \int_{\upsilon_i} \sum_{\widetilde{k}\in J_{t-1}} d_{jt}\left(i,\widetilde{k}\right) s_{jt}\left(i,\widetilde{k}\right) dP_{\upsilon}\left(\upsilon\right) \tag{17}$$

$$\widetilde{s}_{\widetilde{k}t} = \int_{\upsilon_i} \widetilde{d}_{\widetilde{k}t}\left(i,\widetilde{k}\right) s_{jt}\left(i,\widetilde{k}\right) dP_{\upsilon}\left(\upsilon\right) \tag{18}$$

where $s_{jt}\left(i,\widetilde{k}\right)$ is the proportion of consumers of type i that own product $\widetilde{k}$ at the start of period t. The proportion of consumers who own a particular product in the following period is the sum of those who purchase that product in the current period and those who already owned that product and decide not to resell it. In particular:

$$s_{jt+1}\left(i,\widetilde{j}\right) = \widetilde{s}_{\widetilde{j}t}\left(i,\widetilde{j}\right) + \sum_{\widetilde{k}\in J_{t-1}} s_{jt}^{D}\left(i,\widetilde{k}\right)$$

The proportion of consumers who own a one-period old product in $t+1$ is equal to the demand for the new product in the period t. The market size M_t is observed and evolves deterministically over time.

2.1 Inference and identification

The estimation algorithm requires three levels of non-linear optimization. Using an approach similar to Gowrisankaran and Rysman (2006), I combine Berry's (1994) procedure along with the Rust's (1987) fixed point algorithm in order to estimate the relevant parameters of the model. The first level involves the non-linear search over the parameters of the model, which in turn contains two sub-levels of optimization: a fixed point calculation of the mean net augmented flow utilities and the transaction costs, and the calculation of predicted market shares of purchases and ownerships based on consumers' dynamic optimization problems.

Following Berry's (1994) strategy, I specify a GMM criterion function to minimize. Given a value of the unknown parameters I compute the implied error term and interact it with the instruments to form the GMM objective function. Then, I perform a search over all the possible parameter values to find those values that minimize the objective function. In searching over the parameter values, I set the discount factor $\beta = 0.8$. [5] Formally, let $Z = [z_1, ..., z_M]$ be the set of instruments such that

$$E\left[Z'\xi\left(\alpha,\sigma\right)\right] = 0$$

[5] I find that the computational time increases exponentially in the discount parameter.

where $\xi(\alpha,\sigma)$ is the vector of unobserved characteristics for which the predicted market shares equal the observed product shares conditional on parameters and transaction costs. The GMM function is given by:

$$\xi(\alpha,\sigma)' Z\Phi^{-1}Z'\xi(\alpha,\sigma)$$

where Φ is a consistent estimate of $E[Z'\xi\xi'Z]$. The computation of the objective function requires knowledge of the weight matrix, Φ, which in general requires knowledge of either the true value of the parameters or consistent estimates of these. There are several solutions to this problem. I follow Nevo's (2000) two-step approach: I first assume homoscedastic errors and therefore the optimal weight matrix is proportional to $Z'Z$. I can then compute an estimate of the vector (α,σ) and use this estimate to compute a new weight matrix to perform the second and final estimation of the parameters.

Second, in the middle loop, the computation of $\xi(\alpha,\sigma)$ is obtained once the augmented net flow utility is computed using the contraction mapping proposed by BLP:

$$\phi'_{jt} = \phi_{jt} + \psi_1\left(\ln\left(\widetilde{s}_{\widetilde{j}t}\right) - \ln\left(\widetilde{s}_{\widetilde{j}t}\left(a,\phi_{jt},\tau_{jt},\sigma\right)\right)\right) \tag{19}$$

One of the innovations of this paper is to use a similar contraction mapping to pin down transactions costs by looking at the market share of consumer's purchases:

$$\tau'_{jt} = \tau_{jt} + \psi_2\left(\ln\left(s^D_{jt}\right) - \ln\left(s^D_{jt}\left(a,\phi_{jt},\tau_{jt},\sigma\right)\right)\right) \tag{20}$$

where $s^D_{jt}\left(a,\phi_{ijt},\sigma\right)$ and $\widetilde{s}_{\widetilde{j}t}\left(a,\phi_{ijt},\sigma\right)$ are computed from equations (17) and (18) and ψ_1 and ψ_2 are *tuning* parameters. I have found that the speed of convergence of equation (20) is higher than (19), so to avoid instability in the converge process I set $\psi_1 > \psi_2$, and also to set $\psi_2 = 1-\beta$.

From a simple inspection of the probabilities in equations (15) and (16) the intuition behind the identification of transaction costs associated with car purchases should be apparent. If I consider a utility function without random coefficients and the choice of the optimal replacement is observed, then I can derive the following equations:

$$\log\left(d_{jt}\left(\widetilde{k}\right)\right) - \log\left(d_{0t}\left(\widetilde{k}\right)\right) = \phi_{jt} - \tau_{jt} + \beta E\left[EV\left(\phi_{jt+1},\phi_{t+1}\right)|\phi_t,\phi_{jt}\right] - \beta E\left[EV\left(\phi_{t+1}\right)|\phi_t\right]$$

$$\log\left(\widetilde{d}_{\widetilde{j}t}\left(\widetilde{j}\right)\right) - \log\left(d_{0t}\left(\widetilde{j}\right)\right) = \phi_{jt} + \beta E\left[EV\left(\phi_{\widetilde{j}t+1},\phi_{t+1}\right)|\phi_t,\phi_{\widetilde{j}t}\right] - \beta E\left[EV\left(\phi_{t+1}\right)|\phi_t\right]$$

Once the value function are numerically computed, the two market shares differ only because of the presence of the transaction costs. This can be statistically interpreted as an error term that makes the predicted share match the observed ones given ϕ_{jt}. Having a more complicated model would not change the intuition behind the identification of transaction costs. Because I allow for the presence of random coefficients and because the data does not provide information about the good bought in case of replacement, I need to integrate over the consumers' heterogeneity and consumers' endowments at beginning of each period (see equation (18) and (17)). Then, using Berry's (1994) result I can invert the market share for sales and ownership for each product to find the implied mean levels, $\phi_{jt} - \tau_{jt}$ and ϕ_{jt} respectively.[6] The identification of transaction costs follows.

To compute the market shares s^{p}_{jt} and s^{k}_{jt}, I need to integrate over the random coefficient parameters. It is standard in the literature to solve this problem by using simulation techniques. I draw $S \cdot l$ values from a given distribution, where l is the length of the vector (a) and S is the number of simulation draws. For a given vector of a, ξ_{jt} and τ_{jt} $\forall$ j, t and for each drawn υ_i I solve for the inner loop, the solution for which includes the answer to the consumer dynamic programming problem. Conditional on the vector of parameters, I iteratively update the logit inclusive value (9), the value functions (13) and (14), the Markov processes (11) and (12) until convergence. Following Rust's NFXP algorithm I discretize ϕ_{it} and $\phi_{i\widetilde{k}t}$ to solve for (13) and (14). The loop involves the estimates of the parameters ρ and γ from regressions (11) and (12). Then, we use these estimates and the standard error to compute the transition matrix. Potentially it is possible to include other variables such as the age in the state space, but it will substantially increase the computational time.

The identification strategy for the parameters in the utility function is similar to BLP. I allow price to be endogenous to the unobserved term ξ_{jt}, but I assume that product characteristics are exogenous. This last assumption suggests that the regressors are the most obvious set of variables to use as instrument. Then, I use the mean product characteristics for a given brand in the same period, the sum of the values of the same characteristics of other products manufactured by the same firm and the sum of the values of the same characteristics of products manufactured by other firms. These instruments are computed for each car age. The instruments are meant to capture how crowded a product in characteristics space is. In the secondhand market there is no creation of new products so that ceteris paribus the initial quantity of each product is correlated with prices. Hence, I use the initial distribution of each product as an additional instrument for used goods.

In the estimation procedure we can add two extra sets of moment conditions. First, I consider that transaction costs can be explained by a set of regressors z_{jt} such as the characteristics of the cars, the price, the initial distribution of cars, time dummies and so on:

[6] As also pointed by Gowrisankaran and Rysman (2006) the invertibility of market shares is not guaranteed when we consider dynamic demand model. I have not found any problems in terms of multiple equilibria.

$$\tau_{jt}(\sigma) = z_{jt}\,\theta + \varsigma_{jt}$$

I can find a new set of instruments $\widehat{Z}$ and moment conditions to use in the minimization problem

$$E\left[\widehat{Z}'\varsigma(\theta,\sigma)\right] = 0$$

Since, I include the price, which is likely correlated with the error term, among the regressors, I have an endogeneity problem similar to the one above. To overcome this I use a similar set of instruments.[7]

We can also use the information about the consumers' response to the scrappage subsidies plan to add a set of micro moments to the estimation procedure. The dataset provides information about the number of new cars (and hence the share) bought during 1997 and 1998 availing of the government subsidy. Then, I match this share with the probability of replacing a specific used car with a new one, in particular

$$E[\{i\ purchases\ new\ vehicle\ with\ subsidy\}|i\ owns\ a\ 10\ year\ old\ car\ ]$$

This information is useful to identify the random coefficient on the constant term and the price coefficient. It provides information about how many consumers prefers the new goods once they decide to scrap their car for a given amount of subsidy.

The variance covariance matrix is recovered by a block-diagonal structure of the different sets of moment conditions.

As discussed above the identification of the transaction cost for each product j is given by the information about sales data and ownership data, so the model does not determine the size of transaction costs for new cars (at least not in the same way as for used cars). This implies that the augmented net flow utility for new cars, computed using the contraction mapping, possibly includes transaction costs. To control for this potential difference, I include a dummy variable associated with new cars in estimating the process (12). It follows that the computation of the transition matrix and the expected value function are different for new and used cars.

During the estimation process, I need to compute the parameter associated with price non-linearly. This is because I need to account for the fact that only those consumers who owned a 10 year or older car were able to buy new cars at the discounted price under the scrappage-policy regime.[8] Given that the policy was introduced in 1997 for a few months and

[7] More specifically, I am using the same set of instrument used above plus the set of regressors y but the price.

[8] Describing the augmented flow utility in terms of characteristics of the car allows me to keep track of its age.

then renewed again in 1998 for few months, it is safe to assume that it was not anticipated by consumers so we can avoid having to introduce age as a third state variable.[9]

Finally, the presence of heterogenous consumers leads to an initial condition problem. In the first period it is necessary to have the joint distribution of $\widetilde{s}_{\widetilde{k}t}\left(i,\widetilde{k}\right)$. In principle, it is possible to estimate this distribution for a finite number of types of individuals and products. Given the dimensionality problem that this will imply in the model in current form, I assume that the distribution in the first period is the same across products. The implications of such an assumption are still under investigation.

3 Data

The Italian automobile market is the fourth largest market in the world (after the US, Japan, Germany) with about 2 million cars sold every year. Most cars sold are manufactured by the Fiat Group that controls the following brands: Fiat, Lancia, Alfa Romeo, Innocenti, Autobianchi, Ferrari, Maserati. Their overall market share was more then 50% in 1990 and has since then gradually decreased. In 2002 for the first time it fell to below 30%. In that period, the presence of each other firm in the market was significantly smaller: Volkswagen, the second largest manufacturer had about 14% of total market share, Ford between 7% and 11%, Citroen/Peugeot and Renault about 7% each, Opel between 5% and 8%, BMW/Mercedes between 3% and 4%.

The data set covers the period from January 1994 to December 2004 for the Province of Isernia in Italy. I have information on prices and characteristics for all new cars and most popular used cars sold in Italy. This information comes from *Quattroruote,* the main monthly automobile publication in Italy. Quantity data are provided by *ACI*, an association that runs the registration records for the Department of Motor Vehicles in Italy. Information about household income, population and price indexes for inflation are available at the Bank of Italy website and at the National Institute of Statistics website.[10]

For all units in the sample, I observe the initial stock in 1994 and all subsequent individual transactions (sales, scrappage decisions, etc.). For each transaction I observe whether or not a car dealer was involved. I observe the manufacturer, the model, the engine displacement (cc), the horse power, the first registration year and the plate for each car. The data track sales dates for individual cars over time. For the cars scrapped in 1997 and 1998, I have information on whether the owner opted to buy a new car and availed of the government

[9] This last assumption is not very restrictive because the subsidies were awarded to consumers who had owned a car for at least one year. This requirement restricts the possibility that consumers could have modified their replacement behavior, in advance, to take advantage of a law that was not issued yet.

[10] www.bancaditalia.it, www.istat.it

subsidy. If the owner of a car moves to a location outside Isernia or sells it to a buyer living outside the Province, then that particular unit is excluded from the sample in the subsequent periods. It is similarly excluded if the owner decides to scrap the car. Analogous logic applies for cars entering the sample. Given this feature of the data, I do not impose any equilibrium condition on the secondary market.

In 1994, the first period of the sample, I observe an initial stock of 37,384 vehicles. Over the sample period I observe 122,075 transactions net of the transactions made by car dealers. To achieve a manageable dimensionality, I group them into 1089 categories based on the year, on the vehicle's age (0,1,..,10) where 0 stands for a new car and 10 groups together all the cars with age of 10 and more[11], engine displacement (*small* if cc<=1300, *medium* if 1300<cc<=1800, *large* if cc>1800) and origin of manufacturers.[12] In particular, I consider three possible macro-groups of manufacturers:

- the Italian Fiat-Group that controls the following brands (all located in Italy): Fiat, Lancia, Alfa Romeo, Innocenti, Autobianchi, Ferrari and Maserati;
- manufacturers located in Germany: BMW, Mercedes, Volkswagen, Audi, Opel, Ford.
- a residual group that is mostly accounted for by Peugeot, Renault, Seat (the Korean and Japanese manufacturers have a very tiny market share due to the presence of quotas).

Up till 2000 *Quattroruote* provided price information only for cars that were up to 8, or in some cases 9 years old. I fill in the missing prices by assuming for each car model a subsequent depreciation rate (i.e. beyond the 8th or 9th year) equal to the depreciation rate the car experienced in the previous period.

In the empirical analysis, I focus on the market for passenger cars, excluding trucks, vans, minivans, SUVs and luxury cars (like Ferrari, Lamborghini and Porsche), in part, because I do not have price information for them. The total proportion of these cars is less than 2% of the initial stock and about 2% of all the transactions over the 11 years. I do not take into account transactions made by car dealers. Furthermore, I assume that the owners of a 10 year old car receive the market price of that car type irrespective of whether they decide to sell or scrap the car.

[11] I assume that a 10-year old car no longer depreciates and provides the same utility to the consumer. Therefore, I assume that also the price is the same across cars older than 10 years except for the stochastic component ξ_{jt}.

[12] The choice of engine displacement as a key characteristic to identify the different products seems natural in this context for two reasons. First, the scrappage-policies was designed according to this characteristic (as explained later) and second, until 1999 property taxes paid, were based on the size of the engine displacement.

	Mean	Standard Deviation
Population	74114.90	364.33
Income	€21547.10	€3610.16
Family size	2.70	1.23

Table 1: Average Consumers Characteristics for The Provinge of Isernia, 1994-2004

Figure 1 shows the pattern of sales of new cars in the province of Isernia. The total amount of new units purchased suddenly jumped in 1997 when the government introduced the scrappage policy. The scrappage-policy, which involved subsidizing car replacement, was aimed at increasing road safety, reducing environmental pollution and stimulating car sales. From January 1997 until September 1997 the government awarded a bonus, the amount of which depended on the size (engine displacement) of the new replacement bought. The cash subsidy accruing to consumers was conditional on buying a new car and the burden was jointly borne by the government and the car manufacturer. The program was scheduled to expire in September 1997 but was extended till the end of the year. In 1998, a similar scheme, lasting from February to September, was introduced. Notice that the introduction of the subsidies had a bigger impact on the sales of small cc cars. Figure 2 shows the number of used cars traded in the sample. Observe that the purchases of used cars slowed down in 1997 and 1998 and there was a steep increase in the following years. The increase in the number of used cars traded indicates a more active second-hand market over time. I also report the average income per household in the province as well as the total number of individuals older than 18 (see figure 3).

The strength of the model is given by the possibility of estimating, non-parametrically, the transaction costs for different car types to explain replacement behavior in the automobile market. Figure 4 shows resale rates for different car types as a function of vehicle age. It is possible to observe how this pattern changes over time and across products. The vertical axis of each plot shows the observed fraction of vehicles of a particular age purchased in used condition in 1994, 1999 and 2002. The horizontal axis shows the vehicle age. For medium cc Fiat in 1994, the resale rate is low for relatively new cars, peaks when vehicles are 6 or 7 year old and decreases for older cars. In 1999 the resale rate had two peaks— when vehicles were 3 and 10 years old respectively. The changes over time can be due to the effect of the scrappage policy or due to changes in the automobile market of a more structural nature. Figure 5 reports the ratios between resales and stock for different vehicle ages[13] and confirms that resale patterns tend to be quite different for different products. These differences in the resale patterns suggest that transaction costs may differ according to car type and we need

[13]In Figure 6 all cars 10 years or older are grouped togheter.

a flexible model to accurately capture this feature.

4 Results and implications

Tables 2 and 4 present the parameter estimates. Tables 2 reports the parameter estimate associated with the characteristics of the cars as in the utility specification. The term α_i^p is meant to capture the consumer's distaste for price increases. I assume that its distribution varies with income. Therefore, as in BLP (1999), I assume that α_i^p has a time varying distribution that is a lognormal approximation to the distribution of income in the Province of Isernia in each year. In particular, if y_i is a draw from lognormal income distribution, then $\alpha_i^p = \frac{\alpha^p}{y_i}$. In this way α^p is the parameter to be estimated and the price sensitivity is modeled as inversely proportional to income. It contributes negatively to utility, with a base coefficient of -9.349. A person with a mean tastes would obtain a positive flow utility form owning a car (relative to the outside option) with a mean constant term of 3.309. The standard deviation on this coefficient is 2.036 indicating that there is substantial variation in the gross flow utility from a car but that, for most people, this term is nonetheless positive. The age of the car reduces the utility more than proportionally: both coefficients, on age and age squared, have a negative sign. The dummies for the engine displacement show that consumers prefer cars with a higher cc engine. The dummies for the new cars are negative and they potentially capture the size of transaction costs for the new cars that the estimation strategy is not able to identify. Dummies for location suggest that consumers prefer cars produced in Germany the most.[14] The coefficient on the discounted expected price is constraint to be the same as the price coefficient but with opposite sign as in the model.

The expected price is computed as fitted values of a pre-stage regression. These values are obtained when I regress prices on lagged prices, the instruments as in the previous section, a trend variable, the number of sales in the previous period and a dummy for new cars. Table 3 reports the value of the estimates.[15] Observe that these variables have a high explanatory power for predicted future prices.

Table 4 reports the parameter estimates of transaction costs over the second set of variables. Notice that time-dummies display a decreasing trend over time confirming that the used car market became more active. This is consistent with the information displayed in figure 2. The price coefficient is negative, therefore the secondary market is more liquid for more expensive cars. The coefficient associated with the stock of cars present in the market

[14]The higher quality of new and used cars produced in Germany is in line with the findings of Emons & Sheldon (2003) .

[15]Prices and incomeare mesured in 1994 CPI euros.

Parameters	
Mean coefficients	
Constant	3.307† (0.273)
Age	-0.049 (0.048)
Age Square	-0.034† (0.005)
Small cc	-1.648† (0.14)
Medium cc	-1.114† (0.105)
Fiat	-0.226† (0.057)
German cars	0.445† (0.074)
Dummy for new cars with small cc	-4.305† (0.203)
Dummy for new cars with medium cc	-3.019† (0.254)
Dummy for new cars with large cc	-1.896† (0.389)
Non linear coefficients	
Price	-9.351† (0.633)
β·Expected price	9.351† (0.633)
Standard deviation constant	2.036† (0.148)
Standard error in parentheses; statistical significance at 5% level indicated with $\dagger$	

Table 2: Parameter estimates - Product characteristics

is negative and highly significant. This result indicates that having more cars in the market reduces the costs associated with finding the right match. This coefficient captures that portion of the transaction costs that arises because of the search process. The costs are bigger for small cc cars and smaller for medium engine displacement.

Finally, there is a negative coefficient associated with the Fiat dummy. Fiat cars are considered less reliable than German-made cars. Based on this negative relationship between transaction costs and vehicle reliability my model would predict that ceteris paribus less reliable brands are purchased more frequently. A similar interpretation stands for the age coefficeint that is negative. This implication of my model is consistent with the result of Porter and Sattler (1999, tables 6-8) and the stylized fact presented in Hendel and Lizzeri (1999) where no asymmetric information is present in the secondary market.

The magnitude of transaction costs are quite large. About 75% of the times transaction costs are bigger than the prices and 48% of the times they double the prices of the car types considered.[16] This result diverges somewhat from previous results seeing in Stolyarov (2002) where the size of transaction costs were less than 80% of the prices. However, comparing these results at face value might be somewhat misleading because the markets analyzed are

[16] The monetary interpretation of the transaction costs, Tm_{jt}, is given by inverting the following equation: $\frac{a^p}{\bar{y}} Tm_{jt} = \tau_{jt}$, where $\bar{y}$ is the average income observed in the sample.

dependent variable: price in $t+1$	
Parameter	
constant	133.120† (15.091)
Lagged price	.771† (.011)
No. of models in each segment/age	-6.622† (1.298)
No. of models in the same group for segment/age	.443 (.854)
No. of models of different groups for segment/age	-1.266† (.621)
Mean cc in each segment/age	.766† (.197)
Mean cc in the same group for segment/age	.417† (.192)
Mean cc of different group for segment/age	.599† (.118)
Sales	.212 (.212)
Initial distribution	.026† (008)
Age	-.333† (.031)
Age squared	.022† (.003)
Fiat	.181† (.097)
Residual Group	.320† (.157)
Trend	-.071† (.008)
Dummy new cars	-2.227† (.134)
F(15,884)=3613.33, R-sq=0.984	
Standard error in parentheses; statistical significance at 5% level indicated with $\dagger$	

Table 3: Price regression

Transaction costs	
Parameters	
Constant	$13.042^{\dagger}$ (0.643)
Age	-0.112 (0.077)
Small cc	0.14 (0.401)
Medium cc	$-0.95^{\dagger}$ (0.27)
Fiat	$-1.214^{\dagger}$ (0.16)
Residual Group	-0.076 (0.144)
Time dummy 1994	$3.809^{\dagger}$ (0.496)
Time dummy 1995	$3.21^{\dagger}$ (0.406)
Time dummy 1996	$2.628^{\dagger}$ (0.325)
Time dummy 1997	$1.951^{\dagger}$ (0.264)
Time dummy 1998	$1.506^{\dagger}$ (0.246)
Time dummy 1999	$0.73^{\dagger}$ (0.218)
Time dummy 2000	$0.833^{\dagger}$ (0.233)
Time dummy 2001	$1.048^{\dagger}$ (0.228)
Time dummy 2002	$0.806^{\dagger}$ (0.231)
Time dummy 2003	$0.424^{\dagger}$ (0.181)
Initial distribution used cars	$-56.894^{\dagger}$ (7.034)
Price	$-0.398^{\dagger}$ (0.072)
Standard error in parentheses; statistical significance at 5% level indicated with $\dagger$	

Table 4: Parameter estimates - Transaction costs

different. In particular, in Italy there is a higher persistence in the stock of cars held by consumers which may partially account for the observed difference.

As the model relies on the simplifying assumption that consumers base their expectations on the logit inclusive value and the net augmented flow utility, it is important to have an idea of how these statistics evolve over time. Figure 6 shows that there is a general upward trend in the logit inclusive value over time computed at the estimated parameter values. This confirms a general upward trend in the pattern of sales previously underlined. Figure 7 shows how the augmented net utility flow evolves as the car ages. We can see that it is decreasing over time. Figures 8 and 9 investigate the magnitudes of the dynamic response by examining the time path of new car sales and used car sales under different assumptions. The solid line shows the actual sales of new and used cars which of course, also, represent the path of sales generated by the model. The dashed line reports what the time path of sales would be if consumers' logit inclusive value and their valuation for cars did not change over time. The simulation is performed by using the parameter estimates. It is important to observe that were one to ignore the underlying dynamics it would lead to underestimation of sales, especially, in the secondary market. Ignoring the dynamics would give us a relatively constant level of sales in the used car market, whereas we observe an upward trend. This is because consumers do not expect their good to depreciate over time. In the primary market this would have the effect of showing a linear trend in sales which would not capture the reduction in the purchases of new vehicles at the end of the sample period. These findings are in line with the results of Gowrisankaran and Rysman (2006).

5 An application of the Model

The choice of replacement vehicle is one of the key variables in assessing the effects of policies directed at modifying the composition of the stock of vehicles in the market. Hence, the model can help us understand their implications and effects. In particular, in this section, I study the effect of the scrappage program implemented in Italy in 1997 and 1998.

5.1 The scrappage policy

Older-vintage automobiles contribute disproportionately to air pollution for two reasons: the initial quality of their pollution control devices (if any) was not as high as those currently being installed and the efficiency of pollution control devices decreases over time. Consequently, it may be in society's interest to offer owners of these vehicles a subsidy to retire them. Typically, these subsidies were between €500 and €1,500 and eligibility to participate in the program was a function of the vehicle's age (e.g., the automobile must be 10 years old

Starting date	January, 1997	October, 1997	February, 1998
Time in force	8 months	4 months	6 months
Total discount	€775 + €922 €1033+€1229	€775 + €922	€775+€922 €620+€738
Requirements	To scrap a car aged 10 years or more and buy a new one with an equal discount from the manufacturers. The first discount was awarded for a new car with cc<1300 and the second for cc >1300	To scrap a car aged 10 years or more and buy a new one with an equal discount from the manufacturers	To scrap a car aged 10 years or more and buy a new one with an equal discount from the manufacturers. The first discount was awarded for a new with average consumption <7 l/km <7 l/km and average consumption <9 l/km

Table 5: Replacement schemes for cars in Italy during the 1990'

	Small cc	**Medium cc**	**Large cc**	Total
Fiat	694	298	217	1209
German Cars	232	377	45	654
Residual Group	111	167	64	342
Total	1047	832	326	2205

Table 6: Purchases of new cars - 1997

or older).

Scrappage subsidies have been particularly popular in the European Union (EU). During the 1990s, most EU countries offered scrappage subsidies. France, Greece, Hungary, Ireland, Italy, and Spain required that to be eligible for these subsidies, the replacement vehicle had to be new. These policies, called *cash-for-replacement* schemes, were also aimed at stimulating the national car industries. On the other hand, Denmark and Norway as well as the United States and Canada, did not impose any constraints on the type of replacement vehicle — they followed a *cash-for-scrappage* scheme.[17] There has been little work on identifying how scrappage subsidies affect car markets. There has been a debate regarding the overall effects of these policies on car markets and consumers welfare, especially considering that these programs could be expanded in scope and duration.

Table 5 summarizes the main elements characterizing the replacement scheme in Italy. Figure 10 reports the numbers of scrapped cars in each year and shows the effect of the scrappage subsidies. Tables 6 and 7 report the total number of new car purchases in 1997 and 1998 classified according to the manufacturer and the size of the engine displacement.

I use the model to analyze the impact of the replacement scheme implemented in Italy: table 8 reports the numbers of new cars bought with the subsidy and its comparison with

[17] See European Conference of Ministers of Transport Publications (1999), EPA (1998), Hahn (1995) for a comprehensive description of the different scrappage subsidy programs in the United States and Europe.

	Small cc	**Medium cc**	**Large cc**	Total
Fiat	698	196	175	1069
German Cars	304	445	53	802
Residual Group	125	176	90	391
Total	1127	817	318	2262

Table 7: Purchases of new cars - 1998

	1997	**1998**
Purchase of new cars w/subsidy	1449	956
Model prediction	1165	880

Table 8: Effect of the subsidy predicted by the model

the prediction of the model. I do not observe the optimal replacement vehicle chosen by consumers once they avail of this scrappage subsidy. Therefore, I use the prediction of the model to have an idea about these purchases. Figure 11 shows that consumers tend to buy small cars, especially those manufactured by FIAT. This confirms that the policy was successful in helping the national car manufacturer. The results of the simulation are in line with the evidence seen in figure 1 and tables 6 and 7.

The first set of experiments that I perform using the parameter estimates is to look at the impact on new cars purchases under different levels of subsidies. In particular, I consider a 50% reduction in the subsidy followed by an increase of similar proportion ; then I compare these with results previously obtained.

From table 9 it is possible to observe that an increase of the subsidy by 50% leads to an 12% increase in the purchases of new cars, whereas a reduction in the subsidy on a similar scale reduces the new car purchases by one third.

In a separate exercise, I perform a counterfactual analysis to see how the replacement decision would have been different under the two different schemes discussed above. First, I consider the real situation in which the Government awarded a subsidy of €775 plus a bonus of €922 awarded by car manufacturers conditional on buying a new car; in the second I consider the situation in which the Government awarded €755 without any constraints

Subsidy	**Number of new car purchases**
€2545	1303
€1697 (Actual Subsidy)	1165
€848	841

Table 9: Impact on new purchases of different level of subsidies

on the type of replacement vehicle (including whether or not the consumer even choose to purchase a replacement vehicle).[18]

Figure 12 reports the results of the two experiments. The results under the *cash-for-replacement* scheme show that the subsidies increase the demand of new cars. Under the *cash-for-scrappage* scheme the increase in the demand for new cars is smaller and there is also an increase in the demand for used cars, as well as the number of consumers who switch to the outside option, i.e. buy no replacement vehicle. Specifically, about 18% of the owners replace their old car with a new one, 14% buy another used car and the remaining 68% choose the outside option. Interestingly, under the *cash-for-scrappage* scheme the total scrapped cars are about three times the number of scrapped cars in the first regime (3,820 vs. 1,165 over 18,036 eligible cars).

On the other hand it is also evident that it would cost more to implement the cash for scrappage policy. Under the first scheme, the government would receive VAT revenues from new sales estimated at €2,070,000 (about 20% of the value of new cars sold) and incur an expenditure of €860,000 (€775 to each eligible household). Under the cash for scrappage scheme the cost of carrying out the policy would have been much higher, both because of the smaller increase in new car purchases and because of the higher number of scrapped cars. In the model, the revenues are estimated at €1,270,000 and the cost at €3,000,000. To evaluate which policy is more desirable overall it is necessary to compare the additional benefit from the scrappage policy (through the higher level of pollution reduction) with the additional costs incurred. This would be possible only with additional information on valuation of emission reduction and is a potential area for future research.

This application showed how the model can be useful to analyze the effects of different policies aimed at affecting the demand for vehicles in the primary and the secondary market.

6 Conclusion

This paper presents a structural model of dynamic demand for automobiles that explicitly accounts for the replacement decision of consumers in the presence of a second-hand market. The model incorporates the feature that consumer replacement is costly due to the presence of transaction costs. In addition, it allows for rational expectations about future product attributes, heterogeneous consumers with persistent heterogeneity over time and endogeneity of prices. The data set that I use for the estimation, provides information about sales dates for individual cars over time as well as information about prices and characteristics of cars. The nonparametric estimation of the transaction costs is achieved from the difference between

[18] In performing the *cash-for-scrappage* counterfactual, I keep the bonus of €922 awarded by car manufacturers to buy a new vehicle.

the share of consumers that choose to hold a given car type each period and the share of consumers that choose to purchase the same car type in each period. The nonparametric estimation is essential to capture the difference in transaction costs over time and across products. The dynamic aspect of the model and the presence of transaction costs are essential to explain the sales pattern in the primary and in the secondary market. If these costs were ignored, it would not be possible to explain the high persistency in the stock of cars held by consumers. Finally, the model is particularly useful in analyzing the effects of policies directed at modifying the replacement decisions that in turn have an impact on the overall distribution of vehicle holdings.

Future work will involve a variety of robustness check of the basic model. I also plan to analyze firm side behavior and look at further micro level data information in order to improve the estimation procedure. In particular, information about frequency of the replacement for individual cars can be useful in estimating a more flexible model in which transaction costs are also incurred by sellers of durables.

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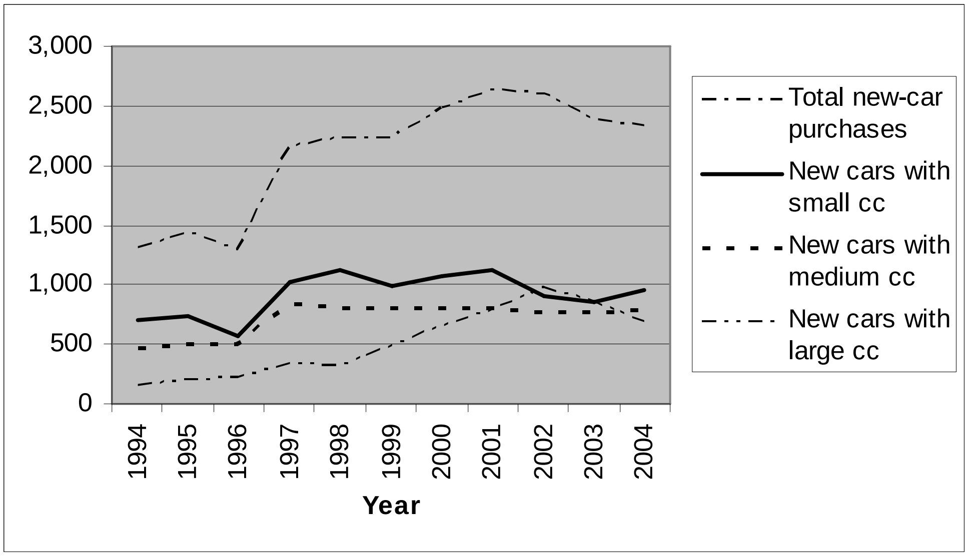

Figure 1- Sales of new cars

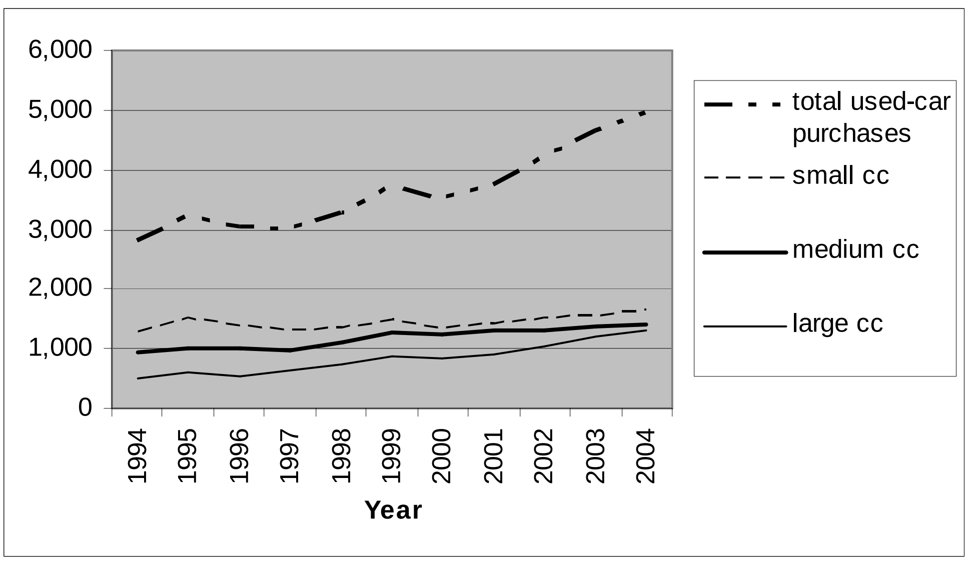

Figure 2 – Sales of used cars

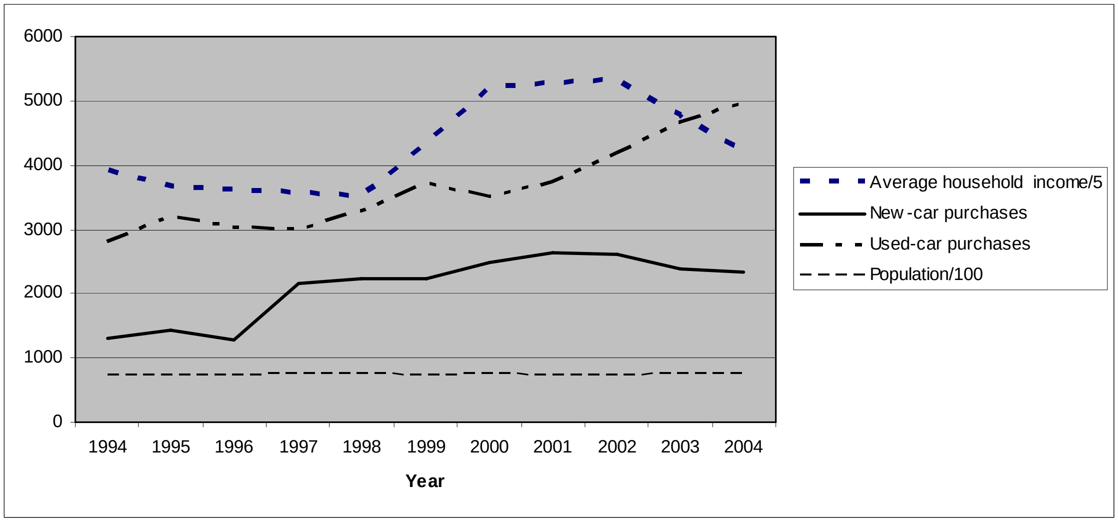

Figure 3: New and used car sales

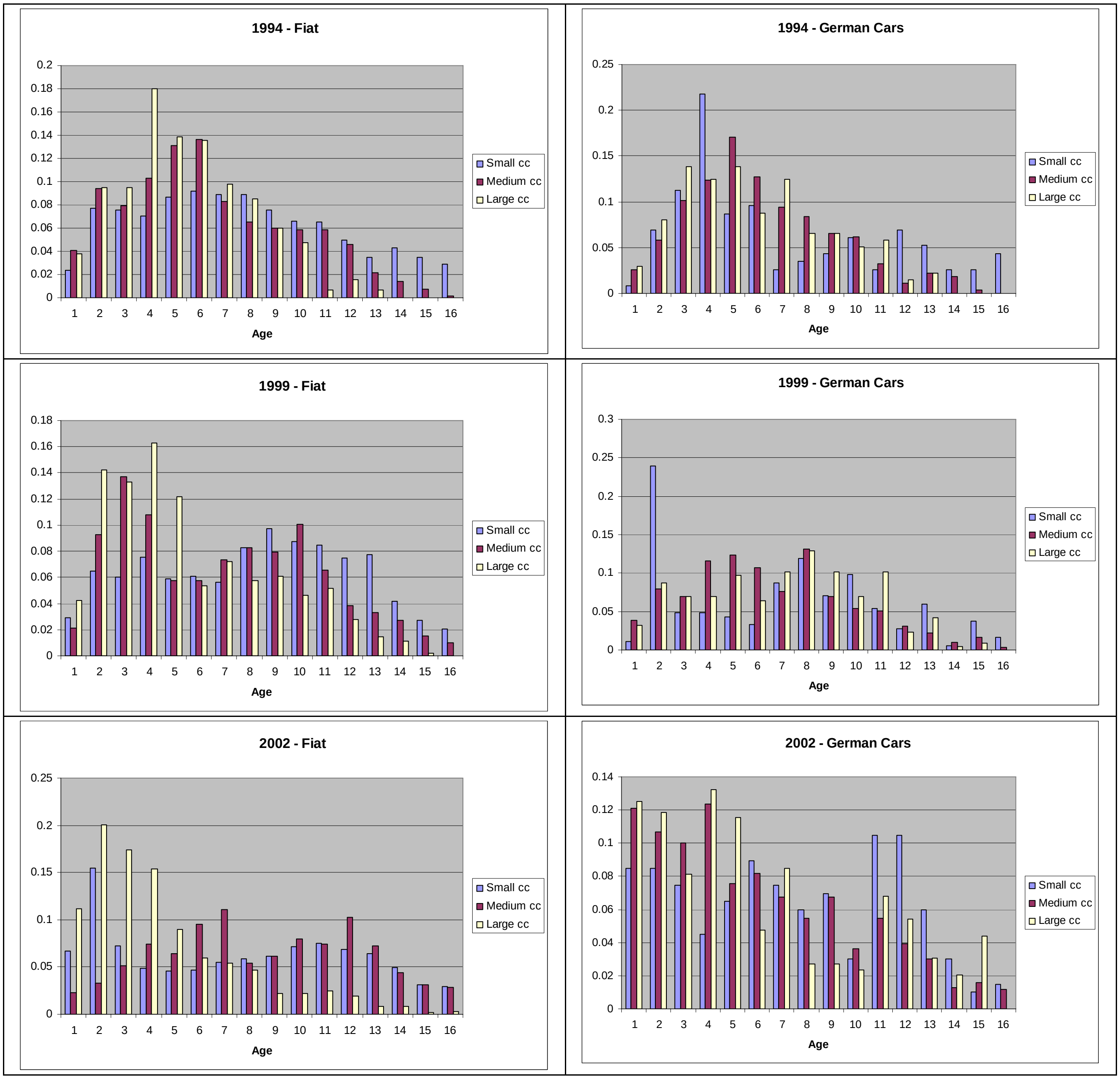

Figure 4: Resale Rate Used Cars

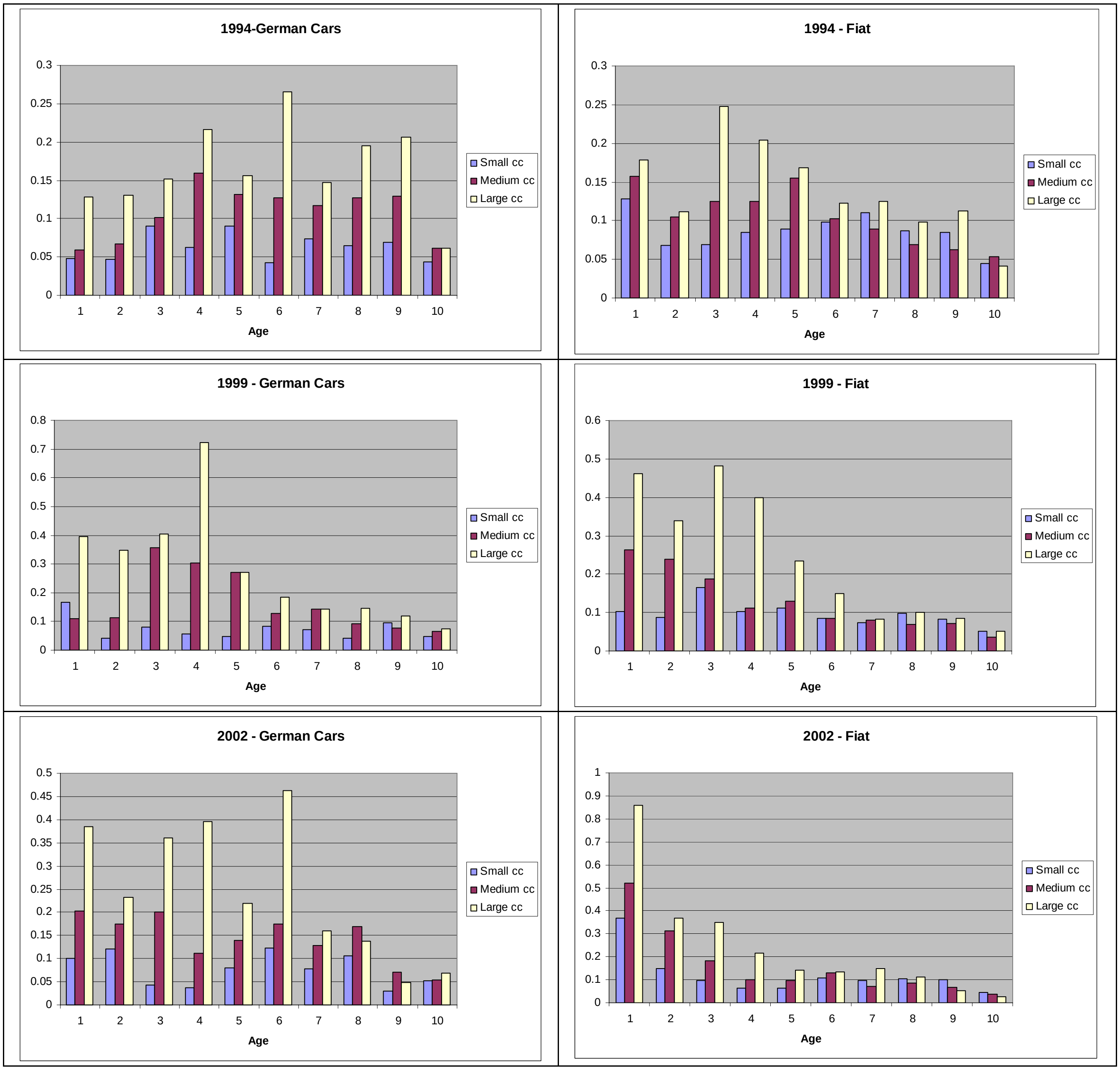

Figure 5: Resale Ratio

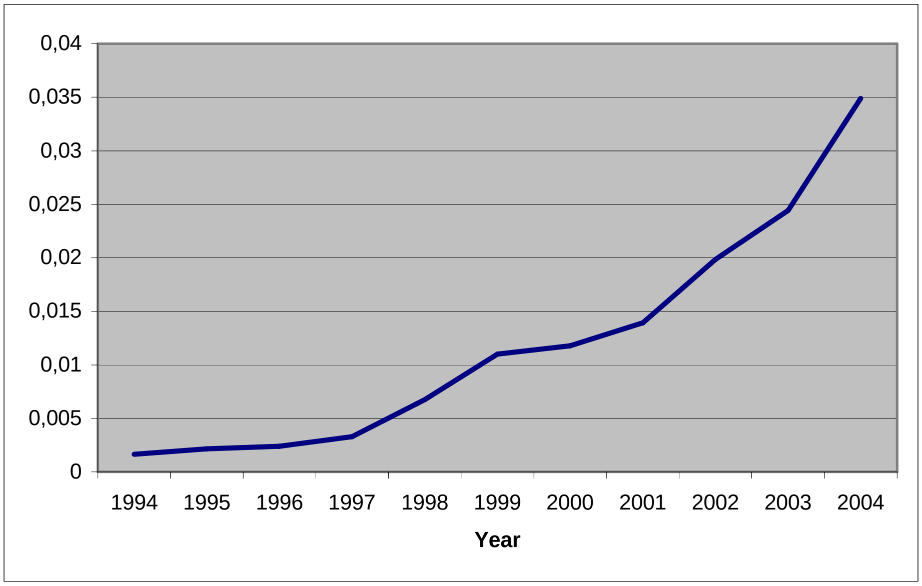

Figure 6: Logit Inclusive Value

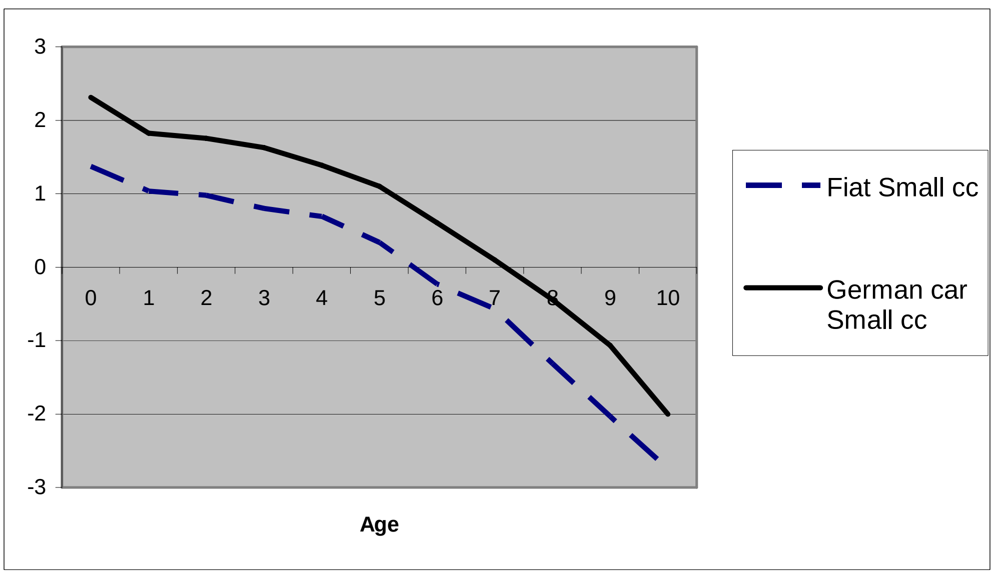

Figure 7: Net augmented flow utility

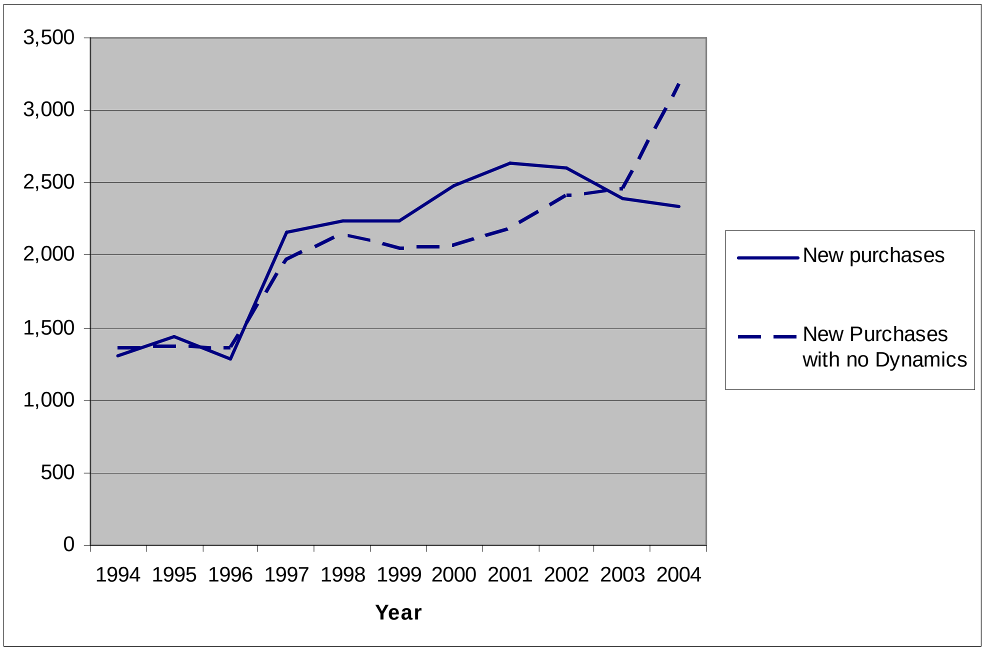

Figure 8: Simulation new purchases

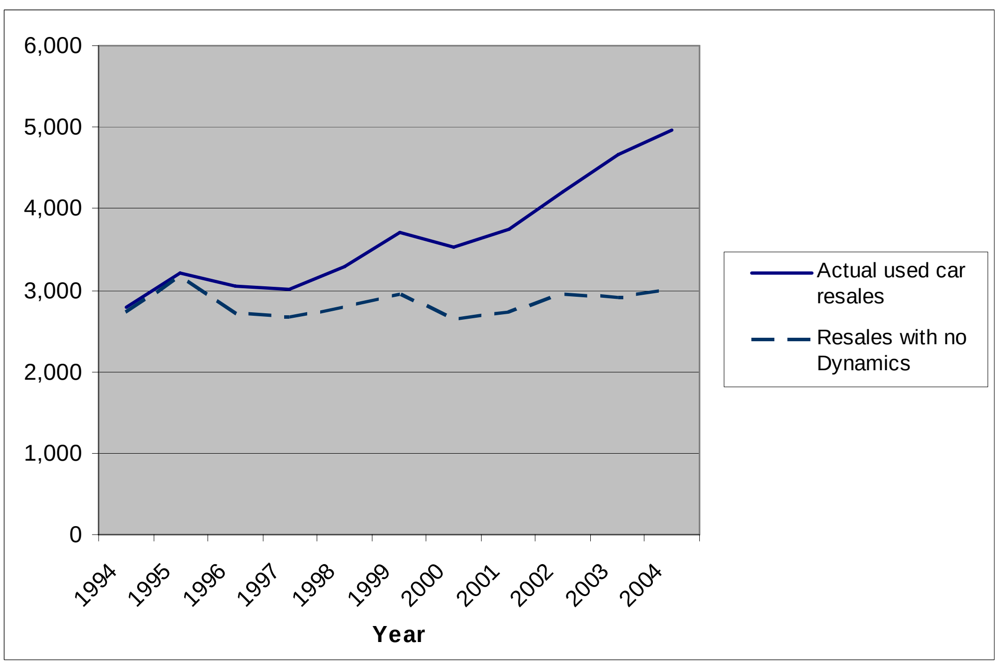

Figure 9: Simulation used car resales

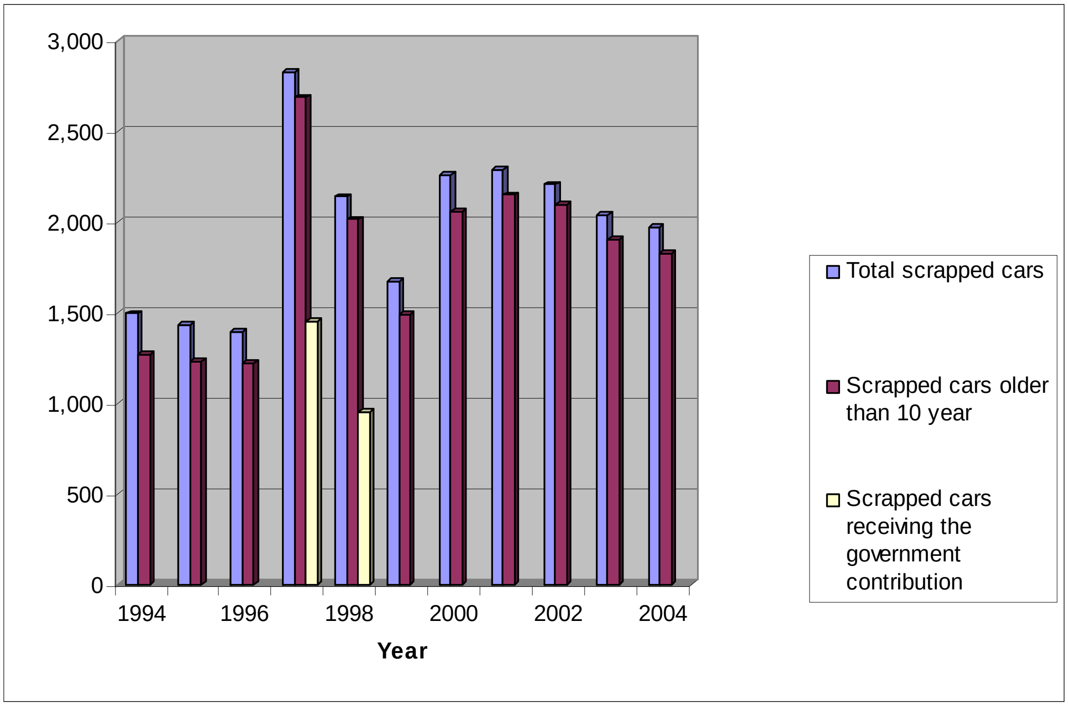

Figure 10: Scrapped cars over time

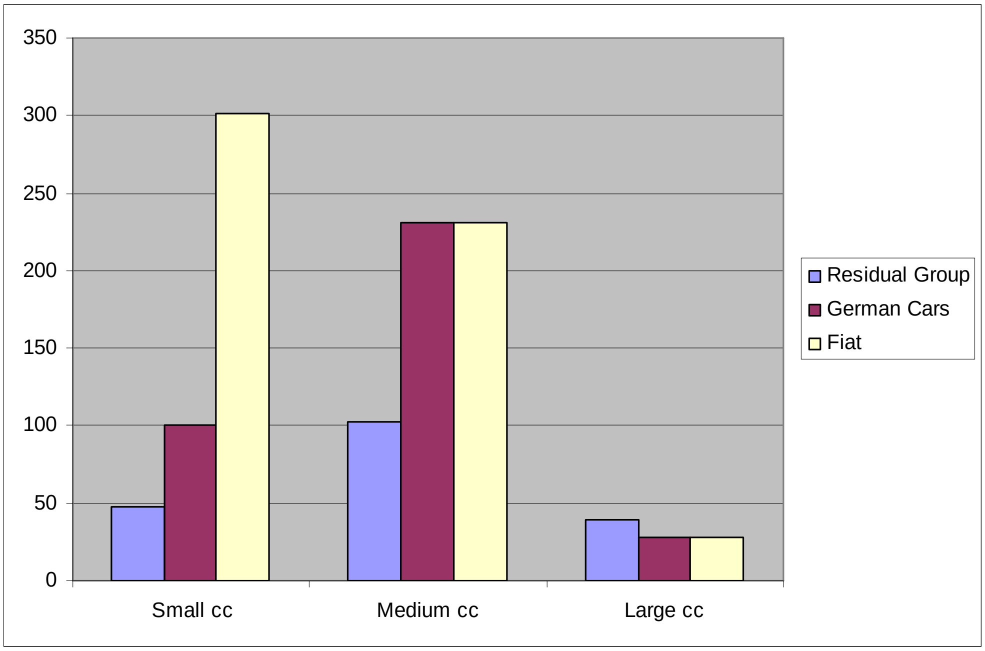

Figure 11: Distribution of new car purchases predicted by the model using the subsidy 1997

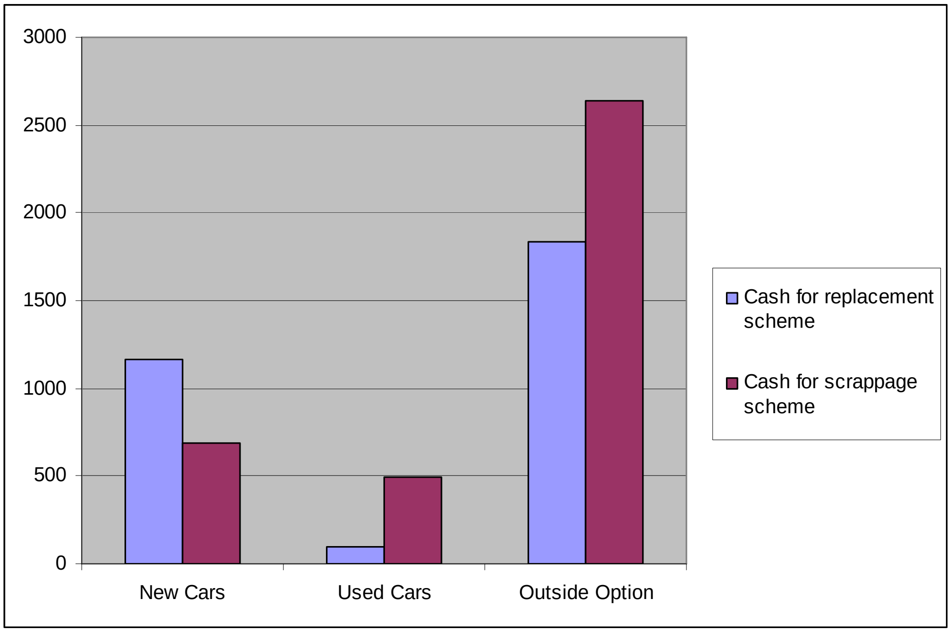

Figure 12: Comparison of the two schemes