Automobile Replacement: a Dynamic Structural Approach*

Pasquale Schiraldi
London School of Economics

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Abstract

This paper specifies and estimates a structural dynamic model of consumer demand 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 unique data set used in this paper has been 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 (1987). I apply this model to evaluate the impact of scrappage subsidies on the Italian automobile market in 1997 and 1998.

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1 Introduction

In many durable good industries, such as that of automobiles, used products are often traded in decentralized secondary markets. The U.S. Department of Transportation reports that in 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 (See Berry, Levinshon and Pakes (1995) —henceforth BLP and 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 and although the auto market is one of the most studied in the literature (Bresnahan (1987), BLP (1995), Goldberg (1995), Petrin (2002)), there have been relatively few empirical models of secondary markets for used goods.

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 search costs, taxes, asymmetric information, switching costs, etc. Transaction costs, essential factors that drive consumer holdings of durable goods, are unobservable and vary over time. If there are no frictions a consumer would choose a quality that maximizes her utility in each period and have no incentive to hold it across multiple qualities/periods. However, these frictions are present and they tend to make replacement infrequent because consumers try to economize on the costs associated with these frictions.

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 explored in the 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. The presence of these two market shares for each car type represents the main strength of my unique data set. These market shares are the results of the consumers' optimal decision that take into account 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 an 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. Transaction costs play a central role in the analysis of market structure and industry conduct for a variety of industries. The proposed methodology can be used to measure transaction costs in the context of other industries as well.

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 in each period. The first market shares refers to the share of consumers who decide to acquire a car j conditioned to buy/replace a vehicle. The market shares of consumer holdings refer to the share of consumers that decide to keep car j conditioned to own that car. 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 model, if transaction costs are paid by buyers, the market share of consumer holdings conveys information on the mean product characteristics, whereas the market share of purchases will, in addition, convey information 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 level 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 the consumer decides to replace her current vehicle. Then, I allow consumers to solve a 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. 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 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 the 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 and he 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. They assume consumer heterogeneity to a single dimension, and do not consider the presence of transaction costs. Having a single dimension and considering a 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. 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 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. 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), Porter and Sattler (1999) and Schiraldi (2009) study vertical differentiated models in which durable goods live for just two periods, so that used goods of all ages are lumped together and derive some testable implications.

Complementary to these works I contemporaneously allow for the presence of heterogenous consumers under multiple dimensions, for the possibility of the price to be correlated with the unobservable characteristics, for the presence of frictions on the secondary market given that durables depreciate over time. I use aggregate data to estimate the demand parameters and the distribution of transaction costs across models and over time.

The remainder 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 $\beta < 1$.

Let $\mathbf{j}_t$ denote the set of new cars available in period t and $J_t = \{j : j \in \{\cup_{\tau=1}^{t} \mathbf{j}_\tau\}\}$ denotes the set of all possible products attainable in period t in the primary or secondary market. In every period there is always the possibility to opt for the outside option, i.e. $j = 0$, which corresponds to not owning a car.

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, immediately upon entering period t the durable depreciates according to the exogenous depreciation process. 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 $J_t \cup \{0\}$ products present in the primary and secondary market in period t (including the outside option). 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} (for example engine displacement, fuel, age, size, etc.), the unobserved (by the econometrician) product characteristic ξ_{jt}, the price p_{jt} and the unobserved (by the econometrician) transaction cost τ_{jt}. I assume that the transaction cost is paid by the consumer (along with the price) every time that she purchases a car and it captures the presence of searching costs, financial costs, switching costs, asymmetric information and so on. No transaction costs are paid if the consumer opts for the outside option.

A consumer who does not hold any product in period t obtains some base flow utility normalized to zero. Moreover, allow 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 may differ on their unobservable characteristics ξ_{jt} and ξ_{jt+1}.

The net utility flow of consumer i at time t is:

$$u_{ijt} = \begin{cases} x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p p_{jt} - \tau_{jt} + \alpha_i^p p_{kt} + \epsilon_{ijt} & \textit{if she buys a replacement, } j \in J_t \\ x_{jt}\,\alpha_i^x + \xi_{jt} + \epsilon_{ijt} & \textit{if she retains the old product, } j \in J_{t-1} \\ 0\ + \alpha_i^p p_{kt} & \textit{if } j = 0 \end{cases} \tag{1}$$

where the first line refers to a consumer purchasing product $j \in J_t$ (and selling good k), the second one to a consumer who owns a good $j \in J_{t-1}$ at the beginning of time t and chooses to retain her existing good and the last to a consumer who does not hold any product in period t and sells product $k \in J_{t-1} \cup \{0\}$ ($p_{kt} = 0$ if $k = 0$). Assume that the error term, ϵ_{ijt}, 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 coefficients. Notice that the preference parameters may vary across consumers, in particular let $\alpha_i^p = \alpha^p + \sigma_{\alpha^p} \upsilon_{i\alpha^p}$ 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 $P_\upsilon(\upsilon)$. Define $\epsilon_{i.t} \equiv \{\epsilon_{i0t}, \epsilon_{i1t}, ..., \epsilon_{iJt}\}$ as the vector of $\epsilon's$ specific to consumer i in periods t.

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.

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. Consequently, the dynamic consumers' optimization problem potentially depends on the whole set of information available in period t and the particular endowment j of each consumer i at time 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. It also depends upon the expectation of the consumer about the evolution of her own good and the set of idiosyncratic utility components for consumer i at period t, i.e. $\epsilon_{i.t} \equiv (\epsilon_{i1t}, ..., \epsilon_{iJ_tt})$.

The main issue in the estimation procedure is the "curse of dimensionality" usually associated with these kinds of problems. To simplify the problem I make some assumptions in line with the existing literature. First, as suggested in Rust (1987), in order to deal with the dimensionality problem associated with the presence of the unobservable $\epsilon_{i.t}$, I define the expectation of the value function integrated over the realizations of $\epsilon_{i.t}$. Then in the spirit of Melnikov (2001), Hendel and Nevo (2006), Gowrisankaran and Rysman (2007), I assume that each consumer in forming her expectations cares about the evolution of the market and the evolution of her own good over time. These two elements are captured by the logit inclusive value and by the net augmented utility flow and correspond to the only two state variables in the value function. Hence I define the net augmented utility flow as

$$\phi_{ijt} \equiv x_{jt}\, \alpha_i^x + \xi_{jt} - \alpha_i^p (p_{jt} - \beta E_t \left[p_{jt+1}\right]) \tag{2}$$

where $E_t \left[p_{jt+1}\right]$ is the expected price for product j in the next period and $(p_{jt} - \beta E_t \left[p_{jt+1}\right])$ is the rental price of car j in period t. The rental price accounts for the cost of keeping a particular good j for a single period of time. The net augmented utility flow, ϕ_{ijt}, captures the flow utility derived by the consumer i from keeping the durable net of the rental price and specifies the location of the durable in a particular state; it includes both elements of consumer characteristics and elements of product characteristics.[1] In a durable-goods setting where the quality of the goods changes over time and there is the possibility of reselling, consumers maximize the utility derived from the good in any particular period net of the implicit rental price paid in that period to keep the good. Hence the net augmented utility flow seems a natural index that captures the per period quality adjusted by the price that consumers account to make their decisions.[2] More specifically, consumers holding product j form expectation about how the value of ϕ_{ijt} evolves over time. Finally the inclusive value for consumer i at time t is:

$$\delta_{it} = \ln \left(\sum_{j \in J_t} \exp \left(\phi_{ijt} - \tau_{jt} + \beta E_t \left[EV_i \left(\delta_{it+1}, \phi_{ijt+1} \right) \right] \right) \right) \tag{3}$$

where $E_t \left[EV_i \left(.\right)\right]$ is the expectation of the value function EV_i (integrated over the realizations of $\epsilon_{i.t}$). The logit inclusive value, δ_{it}, is a sufficient statistic for the distribution of the maximum utility that an agent can achieve over time by replacing his own good with any of the $j \in J_t$ product available.[3] 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 on 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 δ_{it} and ϕ_{ijt}. In general these values could depend on the entire set of information available at time t, but in order to solve the consumers'

[1] Note that for the outside option $\phi_{ijt} = 0$.

[2] The definition of the net augmented utility flow in term of the rental price as in (2) follows from manipulating the Bellman equation (see the appendix).

[3] See Melnikov (2001) for a complete derivation.

dynamic optimization problem, assume that the processes are modeled independently as one-dimensional Markov process. In particular, assume that the Markov processes take the following linear functional form:

$$\delta_{it+1} = \rho_{1i} + \rho_{2i}\delta_{it} + \eta_{it} \quad (4)$$

$$\phi_{ijt+1} = \gamma_{1i} + \gamma_{2i}\phi_{ijt} + \mu_{it} \quad (5)$$

where η_{it} and μ_{it} are standard-normally distributed. It is also straightforward to extend the above processes to allow a quadratic term without increasing the computation time. Similar functional forms have been used in the existing dynamic literature (see Melnikov, (2001); Hendel & Nevo, (2006); Gowrisankaran and Rysman (2007)). This specification amounts to a bounded rationality assumption where consumers have a limited ability to predict the evolution of the future and can only predict partitions of the future state, but are correct on average about the probability of occurrence of each partition. The functional form for the logit value (4) is of potential concern since it is not explicitly generated from supply-side dynamic optimization. For example, δ_{it} could be high either because there are many products in the market all with high prices or because there is a single product in the market with a low price. While dynamic profit maximization might lead these two states to have different patterns of industry evolution, consumers in the model will lump them into the same partition. Similarly equation (5) approximates consumers' ability to predict how the quality of their own goods evolve over time. Notice that equation (5) allows individuals to end up in different states only if they have different random coefficients. This assumption is restrictive in the sense that it 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 different ages is not the same as the aggregate distribution over states.

Using the simplifications above and assuming the error term is Type I extreme value distributed, I can write the Bellman equations for the consumer's optimal decision problem as:[5]

Case-1: consumer with endowment $k \in J_{t-1}$

[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.

[5] A complete derivation of the Bellman equation is provided in the appendix.

$$EV_i\left(\delta_{it},\phi_{ikt}\right)=\ln\left(\begin{array}{c}\underbrace{\sum_{j\in J_t}\exp\left(\phi_{ijt}-\tau_{jt}+\beta E\left[EV_i\left(\phi_{ijt+1},\delta_{it+1}\right)|\delta_{it},\phi_{ijt}\right]\right)}_{=\exp(\delta_{it})}\\+\exp\left(\beta E\left[EV_i\left(0,\delta_{it+1}\right)|\delta_{it}\right]\right)\\+\exp\left(\phi_{ikt}+\beta E\left[EV_i\left(\phi_{ikt+1},\delta_{it+1}\right)|\delta_{it},\phi_{ikt}\right]\right)\end{array}\right) \tag{6}$$

Case-2: consumer without endowment $k=0$

$$EV_i\left(0,\delta_{it}\right)=\ln\left(\exp(\delta_{it})+\exp\left(\beta E\left[EV_i\left(0,\delta_{it+1}\right)|\delta_{it}\right]\right)\right) \tag{7}$$

From (6) and (7), the consumer can choose to wait and keep her current product (possibly $k=0$), or purchase any of the available products $J_t\cup\{0\}$. 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 i with good $k\in J_{t-1}\cup\{0\}$ purchases a good $j\in J_t\cup\{0\}$ is:

$$d_{ijt}^k=$$

$$\frac{\exp\left(\phi_{ijt}-\tau_{jt}+\beta E\left[EV_i\left(\phi_{ijt+1},\delta_{it+1}\right)|\delta_{it},\phi_{ijt}\right]\right)}{\exp(\delta_{it})+\exp\left(\beta E\left[EV_i\left(0,\delta_{it+1}\right)|\delta_{it}\right]\right)+\exp\left(\phi_{ikt}+\beta E\left[EV_i\left(\phi_{ikt+1},\delta_{it+1}\right)|\delta_{it},\phi_{ikt}\right]\right)} \tag{8}$$

Let $\widetilde{d}_{ikt}^k$ denote the probability that a consumer of type i with good $k\in J_{t-1}\cup\{0\}$ chooses not to make a purchase and retain her existing product:

$$\widetilde{d}_{ikt}^k=$$

$$\frac{\exp(\phi_{ikt}+\beta E\left[EV_i\left(\phi_{ikt+1},\delta_{it+1}\right)|\delta_{it},\phi_{ikt}\right])}{\exp(\delta_{it})+\exp\left(\beta E\left[EV_i\left(0,\delta_{it+1}\right)|\delta_{it}\right]\right)+\exp\left(\phi_{ikt}+\beta E\left[EV_i\left(\phi_{ikt+1},\delta_{it+1}\right)|\delta_{it},\phi_{ikt}\right]\right)} \tag{9}$$

Notice that in a state dependent model the two probabilities differs by the presence of the term τ_{jt}, i.e. the transaction costs. More specifically without transaction costs $d_{ijt}^k=\widetilde{d}_{ijt}^k$ for any good j, it follows that consumers' decision no longer depends from having a particular good k (possibly nothing). Moreover, a model without transaction costs cannot explain the systematic difference in the market share of purchases and the market share of holdings for the same used good j (see section 3 and figures 2 and 3). This systematic difference is instead captures by τ_{jt} in the model above.

Integrating d_{ijt}^k and $\widetilde{d}_{ikt}^k$ over consumer preferences and summing d_{ijt}^k over all existing products I compute the market share of each product purchased and the market share for consumer holdings:

$$s_{jt}^{D} = \int_{\upsilon_i} \sum_{k\in J_{t-1}\cup\{0\}} d_{ijt}^{k} s_{ikt} dP_{\upsilon}(\upsilon) \tag{10}$$

$$\widetilde{s}_{kt} = \int_{\upsilon_i} \widetilde{d}_{ikt}^{k} s_{ikt} dP_{\upsilon}(\upsilon) \tag{11}$$

where s_{ikt} is the proportion of consumers of type i that own product k at the beginning 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 own that product and decide not to resell it. In particular:

$$s_{ijt+1} = \widetilde{s}_{ijt} + s_{ijt}^{D}$$

where $\widetilde{s}_{ijt}$ and s_{ijt}^{D} are obtained as in equations (10) and (11) without integrating over the consumer heterogeneity. 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.

In order to deal with the initial distribution of consumer types across different car types, I estimate a dynamic random coefficient model without transaction costs (as I specify in Section 4). Then, I use the resulting distribution of consumer types as the initial distribution of consumers across different car types for the full model estimation.

2.1 Estimation

In this section I offer an overview of the algorithm used to jointly estimate the parameters in the utility function and the distribution of transaction costs. Consequently a further analysis is performed to study the nature of these costs. 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 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. In searching over the parameter values, I set the discount factor $\beta = 0.9$ and the total market size M equal to the adult population in the area. I assume that unobservable product characteristics for each model evolve according to a first-order autoregressive process, where the error term is $\varsigma_{jt} = \xi_{jt} - h \cdot \xi_{jt-1}$ and h is a term to be estimated. The drift of this process is set to 0 since it is not separately identified from the constant in the mean utility. Although observed product characteristics may be endogenous with respect to unobserved characteristics ξ_{jt} and I assume that – with the exception of prices – these observed characteristics will be exogenous with respect to changes in these unobserved characteristics. However, since current prices may be correlated with these innovations in product unobservables, I will use lagged prices as an instrument. Additional instruments in the spirit of Berry, Levinsohn, and Pakes (1995) include own and other product characteristics are used for new products only and the initial stock for each model at the beginning of each period is used for the used cars.

Formally, let $Z = [z_1, ..., z_M]$ be the set of instruments such that

$$E\left[Z'\varsigma\left(\theta\right)\right] = 0$$

The GMM function is given by:

$$\varsigma\left(\theta\right)' ZW^{-1}Z'\varsigma\left(\theta\right)$$

where W is a consistent estimate of $E\left[Z'\varsigma\varsigma' Z\right]$. The computation of the objective function requires knowledge of the weight matrix, W, 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 θ and use this estimate to compute a new weight matrix to perform the second and final estimation of the parameters. The nonlinear search is performed using the direct search method.

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

$$\phi_{jt}^{'} = \phi_{jt} + \psi_1\left(\ln\left(\widetilde{s}_{jt}\right) - \ln\left(\widetilde{s}_{jt}\left(\phi_{jt}, \tau_{jt}, \theta\right)\right)\right) \tag{12}$$

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 consumers' purchases:

$$\left(\phi_{jt} - \tau_{jt}\right)' = \left(\phi_{jt} - \tau_{jt}\right) + \psi_2\left(\ln\left(s_{jt}^D\right) - \ln\left(s_{jt}^D\left(\phi_{jt}, \tau_{jt}, \theta\right)\right)\right) \tag{13}$$

where $s_{jt}^D\left(\phi_{ijt}, \theta\right)$ and $\widetilde{s}_{jt}\left(\phi_{ijt}, \theta\right)$ are computed from equations (10) and (11) and ψ_1 and ψ_2 are *tuning* parameters. I have found that the speed of convergence of equation (13) is higher than (12), so to avoid instability in the converge process I set $\psi_1 > \psi_2$, and $\psi_2 = 1 - \beta$.

From a simple inspection of the probabilities in equations (8) and (9) 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:

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

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

Once the value functions 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 the beginning of each period (see equation (11) and (10)). 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_{jt}^{p} and s_{jt}^{k}, 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. In practice, I used 40 simulated draws computed from the Halton sequence to further reduce the sampling variance (see Gentle, 2003). 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 (3), the value functions (6) and (7), the Markov processes (4) and (5) until convergence. Following Rust's NFXP algorithm I discretize δ_{it} and ϕ_{ijt} to solve for (6) and (7). The loop involves the estimates of the parameters ρ and γ from regressions (4) and (5). Then, I 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.

In the estimation procedure once I recover the transaction costs, I regress these costs on a set of regressors w_{jt} such as the characteristics of the cars, the price, the initial distribution

[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.

of cars, time trend and the unobserved product characteristic ξ_{jt} recovered from the market shares. The estimation sheds light on the nature and composition of transaction costs.

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). In the estimation procedure, I assume that whoever purchases a new car pays taxes and other costs upon registration as specified by *Quattroruote*.[7] These costs vary between €500 and €2000 according to the type of the new vehicle purchased.

During the estimation process, I need to compute the parameters associated with price non-linearly. This is because I need to account for the fact that only those consumers who owned a 10 year old 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 then renewed again in 1998 for a few months, it is safe to assume that the policy was not anticipated by consumers so I can avoid having to introduce age as a third state variable. 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.

Identification of random coefficient parameters relies on the variation in the choice sets at different points in time as well as significant variation in prices.

3 Data

The Italian automobile market is the fourth largest market in the world (after the US, Japan and 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 and Maserati. The FIAT Group's share was more then 50% in 1990 and has since then gradually decreased. In 2002 for the first time it fell below 30%. In that period, the presence of any other firm in the market was significantly smaller: Volkswagen, the second largest manufacturer had a 14% market share; Ford between 7% and 11%; Citroen/Peugeot and Renault about 7% each; Opel between 5% and 8% and 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 of all new and most

[7] The main monthly automobile publication in Italy

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

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.[9] I report in table 1 some demographics of the population.

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 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. Analogously cars coming from outside Isernia are included in the sample in the years following the purchase of these cars. Given this feature of the data, I do not impose any equilibrium condition on the secondary market and I focus on the estimation of the demand side rather than considering a general equilibrium model.

In 1994, the first period of the sample, I observe an initial stock of 32,534 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 2,178 categories based on the year, on the vehicle's age (0,..,10) where 0 stands for a new car and 10 groups together all the cars 10 years or older[10], engine displacement (*small* if cc<=1300, *medium* if 1300<cc<=1800, *large* if cc>1800) and type of fuel: gasoline or diesel and origin of manufacturers.[11] 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 and Porsche

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

[10] 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}.

[11] 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.

- a residual group that is mostly accounted for by Ford, Peugeot, Renault and Seat (the Korean and Japanese manufacturers have a very tiny market share due to the presence of quotas)

Up until 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 and Lamborghini), 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. 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.

Figure 1 shows the pattern of sales of new and used cars in the data. 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 until the end of the year. In 1998, a similar scheme, lasting from February to September, was introduced. 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. The increase in the volume of used cars transactions is explained by the reduction of taxes to pay upon registration over the time horizon considered.

The strength of the model is given by the possibility of estimating the whole distribution of transaction costs for different car types to explain replacement behavior in the automobile market. Figure 2 shows the ratio of car purchases over the car held for some model/year. Figure 2 and table 2 give a clear idea of the presence of transaction costs. Without frictions that ratio should be not statistically different from 1, whereas it is possible to observe that the number of people who keep their car is substantially greater than those who decide otherwise. Figure 3 shows resale rates for different car types as a function of the 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, 1998 and 2004. These differences in the resale patterns suggest that transaction costs differ according to the car type and we need a flexible model to accurately capture this feature.

4 Results and Implications

Tables 3 and 4 present the parameter estimates. Table 3 reports the parameter estimate associated with the characteristics of the cars as in the utility specification. Signs of coefficients are as expected, with utility decreasing from the price and the age of the car. The estimation of the full model is performed allowing for 2 random coefficients respectively the (rental) price and the age. In the estimation procedure, I do not attempt to estimate two separate coefficients for the price and the expected price due to potential collinearity issues. Hence, I will refer as price coefficient, the coefficient estimated for the rental price $(p_{jt} - \beta E_t [p_{jt+1}])$. The price coefficient is estimated non linearly due to the possibility of implementing the scrappage policy for owners of 10-year old cars in 1997 and 1998 and the magnitude is -4.81. The heterogeneity in price sensitivity is captured by the term σ_i^p. Recall that σ_i^p is the coefficient on consumers' annual income and not the standard deviation of the distribution. In particular, I assume that σ_i^p has a time varying distribution, i.e. given that y_i is a draw from the empirical income distribution, then $\sigma_i^p = \frac{\sigma^p}{y_i}$. In this way σ^p is the parameter to be estimated and the price sensitivity is modeled as inversely proportional to income. A consumer obtains a positive flow utility from owning a car (relative to the outside option) with a mean constant term of 13.42. The age of the car reduces the utility. σ^{age} captures the heterogeneity in taste for age among consumers. The coefficient of 2.76 evidences that consumers prefer cars with a higher cc engine. Dummies for location suggest consumers' preference for German cars.[12] The coefficient on the discounted expected price is constrained to be the same as the price coefficient but with opposite sign as in the model. The dummy on fuel shows that people prefer gasoline rather then diesel engine. The positive coefficient on the fuel dummy interacted with time trend is capturing the increasing utility over time to buy diesel cars. Over the time window considered, there is a substantial reduction in the taxes owed to the government especially for diesel engine cars; the model is able to capture the increasing appeal for these vehicles due to this tax reduction.[13]

Future resales prices are needed to obtain rental price each year. Since these future prices are not available for all years, I use a pre-stage price regression to predict these values. These values are obtained when I regress prices on lagged prices, characteristics of cars and a time

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

[13] In particular, the property tax fell progressively by more than 50%.

trend. Table 4 reports the value of the estimates.[14] Observe that these variables have a high explanatory power for predicted future prices.

In Table 3, I also compare the results from the main model as in section 2 with the estimations of a dynamic model with no transaction costs and of a model with no dynamics. The last column represents a static BLP model when consumers choose between different types of new and used cars and they no face any dynamic decision and they do not pay any transaction costs. In the second column I estimate a dynamic model without the transaction costs. The dynamic model without transaction costs has a simple analytical solution. For each consumer i the probability of choosing alternative j given $k \in J_{t-1} \cup \{0\}$ is

$$d_{ijt}^{k} = \frac{\exp(x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p p_{jt} + \alpha_i^p p_{kt} \cdot I(j \neq k) + \beta E_t\left[EV_{ij}\left(...\right)\right])}{\sum\limits_{j \epsilon J_t \cup \{0\}} \exp(x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p p_{jt} + \alpha_i^p p_{kt} \cdot I(j \neq k) + \beta E_t\left[EV_{ij}\left(...\right)\right])}$$

If there are not transaction costs the problem is no longer state dependent and $E_t\left[EV_i\left(k,.\right)\right] = E_t\left[EV_i\left(0,.\right) + \alpha_i^p p_{kt+1}\right]$.[15] Replacing the previous equality in the discrete choice probability and simplifying it we obtain:

$$d_{ijt} = \frac{\exp(x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p (p_{jt} - \beta E_t\left[p_{jt+1}\right]))}{\sum\limits_{j \epsilon J_t \cup \{0\}} \exp(x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p (p_{jt} - \beta E_t\left[p_{jt+1}\right]))}$$

Then the dynamic model without transaction costs is similar to BLP, where among the regressors we have also the expected price for each vehicle. As previously discussed in a model without transaction costs, the probability of keeping any car j is exactly the same as the probability of buying it and no systematic difference between these two shares in the data can be explained. The comparison confirms that the results and the implications of the models are substantially different. If I do not account for the presence of transaction costs in a dynamic setting the estimates are quite different and in particular I obtain a non significant price coefficient. Figures 4 and 5 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 represents 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

[14] Prices and income are measured in 1994 CPI euros.

[15] Notice that $EV_i\left(0,.\right)$ no longer depends from the good held by consumers and it is constant across products

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.

As in Figure 6, the magnitude of transaction costs decline over time.[16] The effect is the result among other factors of a progressive reduction of the taxes paid upon the transaction and a reduction of the interest rate due to the introduction of the European currency. The average transaction cost was about €3000 in 1994 decreasing to €1800 in 2004[17].

This measures the total amount of transaction costs paid by both the buyer and the seller upon a transaction of a used car. The distribution of transaction costs is shown in figure 7; it shows a peak in the level of transaction costs between €1400 and €2200. The minimum level of the cost is about €1000.

If we compute the fraction of transaction costs over prices of different car-types we can observe (Figure 8) that there is a peak between 20% and 40% and most of the models show a level of transaction costs between 10% and 80% of the respective level of prices. About 25% of models exhibit a level of transaction costs higher than the prices. These models are mostly old cars of 8 years or above where we observe a limited number of transactions. As in Figure 3 the number of transactions for these cars is less than 8% of the total stock of vehicles available of the same kind. However, it is important to notice that the estimates do not refer to the costs that are actually paid upon transaction, but rather to the costs of hypothetical purchase of a particular car j. In the model, people choose to buy a car only when the payoff shocks are favorable. The unexplained part of the utility flow, ϵ_{ijt}, may be viewed as either a preference shock or a shock to the cost, with no way to distinguish between the two. The net cost paid upon a transaction is therefore less than the amounts above reported.

The level of transaction costs explains the high persistence in the stock of cars held by consumers. The results imply that on average, a consumer keeps her automobile for about 7 years. This result is obtained without accounting for the truncations in the data. Do these figures make sense? According to the information published in the magazine *Quattroruote* in 1998, the explicit costs to sustain upon a transaction of a used car varies between €1000 and €4000. The composition of these costs is the following: financial costs about €400; *Quattroruote* reports that on average, the money borrowed to buy a used car in 1998 was €5000 and the spread over a safe interest rate was about 8%. The taxes and expenses to pay

[16] The estimate of the transaction costs are relative to the used cars only. For the new cars, I cannot identify the size of the transaction costs. In the estimation procedure, I assume that whoever purchases a new car pay taxes and other costs of registration as specified by *Quattroruote*. These costs vary between €450 and €800 according to the type of the new vehicle purchased.

[17] The monetary interpretation of the transaction costs is obtained by dividing the estimated transaction costs by the price coefficients.

upon the transaction varied between €340 and €1600 according to the size and the type of cars. The dealer compensation for trading a used car also varied between €300 and €2000 according to the model. On top of that we need to account for the hidden costs like search costs, asymmetric information and so on. The above analysis confirms that the estimations of the model seem to have the right magnitude and transaction costs as expected to play a substantial role in consumers' replacement decision. In Table 6, I compare the transaction cost estimates with the taxes and the dealer compensations as reported in *Quattroruote* relative to few models.

The difference can be explained by the presence of financial costs, search costs and similar costs sustained also by the seller of a used car.

Next I try to investigate in more detail the composition of the transaction costs. Table 5 reports the parameter estimates of transaction costs over a second set of variables. We can observe that the coefficient associated with the stock of each car type in percentage terms is negative and highly significant. This result indicates that having more cars in the market reduces the costs associated with finding the right match. More specifically, an increase of 1% in the stock of cars available reduces the transaction costs by €70. This relation captures one of the essential characteristics of a decentralized market: traders must incur costs to search for trading opportunities. Thinner markets cause higher search costs. Instead, the matching between buyers and sellers becomes easier in a thicker market where larger stocks of cars are available. In this sense, cars with a thicker market are more liquid. The reason is that cars with a thin market are more difficult to sell, and they have higher option values: consumers choose to hold on to them for longer periods. Hence as expected the transaction costs decreases in the stock of each type of car available. Moreover, the effect of trading frictions transmits to transaction prices by decreasing on average their level, i.e. cars with lower transaction costs have higher average levels of price.

The variable *Diesel*Time trend* captures the reduction of taxes over time relative to the car with Diesel engines as discussed above. The costs are increasing in the engine displacement, as higher taxes and fees are usually associated with bigger cars. Notice the transaction costs display a decreasing trend over time confirming that the used car market became more active. This is consistent with the information displayed in Figures 1 and 2. The effect is the result of a progressive reduction in the taxes to pay upon the registration, the enhancement of Internet transactions and the introduction of the Euro —and the consequent reduction of the interest rate and transaction costs across EU countries.

Finally, there is a negative coefficient associated with the FIAT dummy. This coefficient might reflect the possibility of having lower maintenance costs associated with the national manufactured cars that reduces the risk of buying a used vehicle that may reveal to be a lemon.

It is further interesting to examine the results attached to the variable that measures the percentage of scrapped cars over the total stock of cars for each type. This can be interpreted as a measure of the reliability of a car. As we can see the transaction costs decrease as this proxy for reliability decreases (the percentage of scrapped cars increases). 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 and hence no presence of adverse selection is detected in the used car market. In the transaction costs regression I allow for the transaction costs to be correlated with the unobservable characteristics of the car-type. This variable is positive correlated with the transaction costs and explains part of the magnitude of these costs.

5 The Scrappage Policy in Italy

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 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.[18] There has been little work on identifying how scrappage subsidies affect car markets. There has been a debate regarding the overall effects

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

of these policies on car markets and consumers' welfare, especially considering that these programs could be expanded in scope and duration.

Table 7 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.

Using the framework developed in and estimates obtained from the previous section, I proceed in this section to examine the prediction of 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 the prediction of the model. The model slightly underestimates the effect of the policy. This is due to the presence of further discounts awarded by the car manufacturers to consumers willing to replace their old cars, which are not available in the data.

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 reports the total number of new car purchases in 1997[19] classified according to the manufacturer and the size of the engine displacement and shows that consumers using the scrappage subsidies mostly buy small cars, especially those manufactured by FIAT. This confirms that the policy was successful in helping the national car manufacturer.

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 €500 without any constraints on the type of replacement vehicle (including whether or not the consumer even chose to purchase a replacement vehicle).[20] The results of these two experiments are reported in Fig. 10. First notice that the *cash-for-scrappage* scheme has a bigger impact on the scrappage decisions because it does not impose any constraint on consumers' decision. With a third of the amount of the subsidy, the *cash-for-scrappage* scheme has a similar effect on the total number of cars scrapped as the *cash-for-replacement* scheme (1,985 vs. 2,300 over 18,036 eligible cars). Moreover as expected, under the cash-for-replacement scheme the subsidies increase mostly the demand for new cars. Under the cash-for-scrappage scheme, instead, the increase in the demand for new cars is smaller and there is a significant impact on the demand for used cars, as well as the number of consumers who switch to the outside option,

[19] The results show a similar effect in the new car purchase in 1998.

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

i.e. buy no replacement vehicle. Specifically, about 8% of the owners replace their old car with a new one, 26% buy another used car and the remaining 65% choose the outside option.

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 €3,756,000 (about 20% of the value of new cars sold) and incur an expenditure of €1,824,000 (€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 €3,280,000 and the cost at €1,154,000 with €500 awarded to consumers.

In order to measure the change in consumer welfare under different subsidy schemes, I compute the compensating variation for consumers who are predicted to take advantage of the subsidies in each of the different schemes discussed above. In the first regime, the *cash-for-replacement* scheme implemented by the government, I find that total consumer welfare increases by approximately €3,850,000. Under the *cash-for-scrappage* scheme, I find that the change in consumer welfare is about €1,100,000.

One caveat about the welfare analysis it that by assumption the policy has no immediate effect on the price of new and used cars. That can be reasonable if we consider an experiment carried out in a particular geographical area for a limited amount of time. In order to account for the change in prices we need a general equilibrium model that imposes the equilibrium condition between supply and demand.

Of course the analysis does not account for the different benefits that the two policies have through the level of pollution reduction or the effect on the employment rate. From the previous section it can be observed that these policies have a quite different impact on the number of used cars scrapped and on the number of new cars purchased. However, a more complete analysis can be performed and the optimal scrappage scheme computed with additional information about the valuation of emission reduction and unemployment and this is a potential area for future research.

Finally, notice that the *cash-for-scrappage* scheme has similar effect on the automobile market as a reduction of transaction costs of the same magnitude, €500. Hence the government could achieve the same results by temporally reducing the taxes to pay upon transactions or by making the secondary market more liquid by improving competitions among dealers and/or reducing the search costs. Interesting it would be to study the impact of internet penetrations on the size of transactions costs.

6 Concluding Remarks

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 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 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 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. It would also be interesting to analyze the nature of adverse selection across different countries/regions and across time accounting for the introduction of more direct sales method as the Internet or how the car dealers effect the information structure of the market and the related costs.

Appendix

In the appendix I derive explicitly the equations (6) and (7). Using the same notation as in Gowrisankaran and Rysman (2007), let Ω_{ijt} represent all the information available to consumer i in period t, including the characteristics about her own endowment $j \in J_{t-1} \cup \{0\}$ and assume that Ω_{ijt} evolves according to some Markov process $P\left(\Omega_{ijt+1}|\Omega_{ijt}\right)$. As in Rust (1987) define the expectation of the value function integrated over the realizations of $\epsilon_{i.t}$ as:

$$\widehat{EV}_i\left(\Omega_{ijt}\right) = \int_{\epsilon_{i.t}} V_i\left(\epsilon_{i.t+1}, \Omega_{ijt+1}\right) dP_\epsilon \tag{14}$$

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 (Ω_{ijt}). Then it is possible to write the Bellman equation that defines the consumer's decision problem as follows:

Case-1: consumer with endowment $k \in J_{t-1}$

$$\widehat{EV}_i\left(\Omega_{ikt}\right) = \log \left(\begin{array}{c} \exp\left(x_{kt}\,\alpha_i^x + \xi_{kt} + \beta E_t\left[\widehat{EV}_i\left(\Omega_{ikt+1}\right)\right]\right) + \\ \sum_{j \in J_t} \exp\left(x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p p_{jt} - \tau_{jt} + \alpha_i^p p_{kt} + \beta E_t\left[\widehat{EV}_i\left(\Omega_{ijt+1}\right)\right]\right) \\ \alpha_i^p p_{kt} + \exp\left(\beta E_t\left[\widehat{EV}_i\left(\Omega_{i0t+1}\right)\right]\right) \end{array} \right) \tag{15}$$

or

Case-1: consumer with endowment $k \in J_{t-1}$

$$\widehat{EV}_i\left(\Omega_{ikt}\right) - \alpha_i^p p_{kt} = \log \left(\begin{array}{c} \exp\left(x_{kt}\,\alpha_i^x + \xi_{kt} - \alpha_i^p p_{kt} + \beta E_t\left[\widehat{EV}_i\left(\Omega_{ikt+1}\right)\right]\right) + \\ \sum_{j \in J_t} \exp\left(x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p p_{jt} - \tau_{jt} + \beta E_t\left[\widehat{EV}_i\left(\Omega_{ijt+1}\right)\right]\right) \\ + \exp\left(\beta E_t\left[\widehat{EV}_i\left(\Omega_{i0t+1}\right)\right]\right) \end{array} \right) \tag{16}$$

Case-2: consumer without endowment $k = 0$

$$\widehat{EV}_i\left(0, \Omega_{i0t}\right) = \log \left(\begin{array}{c} \exp\left(\beta E_t\left[\widehat{EV}_i\left(\Omega_{i0t+1}\right)\right]\right) + \\ \sum_{j \in J_t} \exp\left(x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p p_{jt} - \tau_{jt} + \beta E_t\left[\widehat{EV}_i\left(\Omega_{ijt+1}\right)\right]\right) \end{array} \right) \tag{17}$$

where p_{kt} is the price that a consumer gets on the used car market once she decides to replace her good k with one of the $J_t \cup \{0\}$ good available on the primary or secondary market (including the outside option). To simplify the dynamic optimization problem and reduce the state space that will reduce the computational burden of the model, it is convenient to define

$$EV_i(\Omega_{ijt}) = \widehat{EV}_i(\Omega_{ijt}) - \alpha_i^p p_{kt} \tag{18}$$

so that we can rewrite the above equation as

Case-1: $k \neq 0$

$$EV_i(\Omega_{ijt}) = \log\left(\begin{array}{c} \exp\left(\underbrace{x_{kt}\,\alpha_i^x + \xi_{kt} - \alpha_i^p(p_{kt} - \beta E_t[p_{kt+1}])}_{=\phi_{ikt}} + \beta E_t[EV_i(\Omega_{ijt+1})] \right) + \\ \underbrace{\sum_{j\in J_t} \exp\left(x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p(p_{jt} - \beta E_t[p_{jt+1}]) - \tau_{jt} + \beta E_t[EV_i(\Omega_{ijt+1})]\right)}_{=\phi_{it}} \\ + \exp\left(\beta E_t[EV_i(\Omega_{ijt+1})]\right) \end{array} \right) \tag{19}$$

Case-2: $k = 0$

$$EV_i(0, \Omega_{ijt}) = \log\left(\begin{array}{c} \exp\left(\beta E_t[EV_i(\Omega_{ijt+1})]\right) + \\ \sum_{j\in J_t} \exp\left(x_{jt}\,\alpha_i^x + \xi_{jt} - \alpha_i^p(p_{jt} - \beta E_t[p_{jt+1}]) - \tau_{jt} + \beta E_t[EV_i(\Omega_{ijt+1})]\right) \end{array} \right) \tag{20}$$

Once the net augmented utility flow and the logit inclusive value are defined we can easily obtain (6) and (7). It is useful to observe that the change in variable as in (18) allow me to rewrite the flow utility of each choice j also in term of the expected price of j rather than the selling price from selling car k ($k \neq j$) owned at the beginning of each period. The definition of the net augmented utility flow follows from the previous equations.

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	Mean	St. Deviation
Population	74114	363..33
Income per Household	€21547	€3610
Family Size	2.70	1.23

Table 1: Consumers Characteristics. Isernia 1994-2004

	Mean	Std
Resale ratio	0.185	0.2667
N. Obs.		1648

Table 2 – Resale Ratio

Estimation Results: Utility

PARAMETERS	Dynamic Model	Dynamic Model with no Transaction costs	Static Model
Constant	13.42^{*} (1.89)	-4.8^{*} (2.47)	-4.28 (5.07)
Log(Age)	-5.31^{*} (0.86)	0.014 (1.22)	-1.69 (1.69)
Engine size (CC)	0.98^{*} (0.4)	-0.16 (0.16)	0.1 (13)
Fiat	0.1 (0.24)	0.83^{*} (0.12)	0.68^{**} (0.06)
German	2.76^{*} (0.33)	-0.44 (0.42)	0.48^{*} (0.36)
Diesel	-1.71^{*} (0.68)	-1.37^{*} (0.45)	-1.23^{**} (0.13)
Diesel*Time trend	0.32^{*} (0.11)	0.23^{*} (0.08)	0.21^{**} (0.02)
NON LINEAR PARAMETERS			
(Price- Expected Price)	-4.81^{*} (0.28)	0.39 (0.62)	-
Price	-	-	0.41 (0.55)
(Price- Expected Price)/Income	-4.1^{*} (1.09)	10.86^{*} (1.72)	-0.47 (3.23)
Log(Age) (standard deviation coefficient)	0.14^{*} (0.07)	0.52 (1.60)	-0.01 (4.48)

Standard errors in parentheses; statistical significance at 5% level indicated with *, and at 10% with **

Table 3: Parameter Estimates

Price Regression

Variable	Coefficient	Std. Err.
Lagged price	0.6179	0.0115*
Time trend	-0.0639	0.0125*
Vintage	-0.2716	0.0191*
Fiat	0.0038	0.069
German	0.6133	0.0721*
Diesel	-0.2479	0.1273**
Diesel*Time trend	0.0281	0.0198
Cc	0.9009	0.0946*
Dummy_10y	0.7801	0.1156*
Constant	128.5296	25.0484*
Number of obs.		1648
Adj R-sq		0.9327

Standard errors in parentheses; statistical significance at 5% level indicated with *, and at 10% with **

Table 4 – Price Regression

Transaction Costs

PARAMETERS	
Constant	20.34* (0.53)
Age	-1.35* (0.11)
Age^2	0.05* (0.01)
Engine size (CC)	0.12 (0.1)
Fiat	-1.14* (0.12)
German	2.06 (0.15)
Diesel*Time trend	-0.04* (0.01)
Initial Stock	-3.34* (0.33)
Scrapped cars	5.31* (1.34)
Time Trend	-0.76* (0.05)
Price	-0.59* (0.12)
ξ_{jt}	0.32* (0.02)

Standard errors in parentheses; statistical significance at 5% level indicated with *, and at 10% with **

Table 5: Parameter Estimates – Transaction Costs

Model	**Year**	**Age**	**Taxes+Dealer Compensation**	**Transaction Costs: Estimates**
Alfa 156 1.6i	1999	1	€ 1675	€ 2500
BMW 318i	1999	3	€ 1700	€ 2180
Fiat Punto 1.9 D	2003	2	€ 950	€ 1450
Audi A3 1.6	2003	5	€ 1450	€ 2490

Table 6: Transaction Costs - Examples

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
Requirement	To scrap a car aged 10 years or older 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 older and buy a new one with an equal discount from the manufacturers	To scrap a car aged 10 years or older and buy a new one with an equal discount from the manufacturers. The discounts were awarded espectively for a new with average consumption <7 l/km and average consumption <9 l/km

Table 7: Replacement Schemes in Italy

	Year 1997	**Year 1998**
Purchase of new cars w/subsidy	2292	1782
Model prediction	*1980*	*1616*

Table 8: Effect of the subsidies

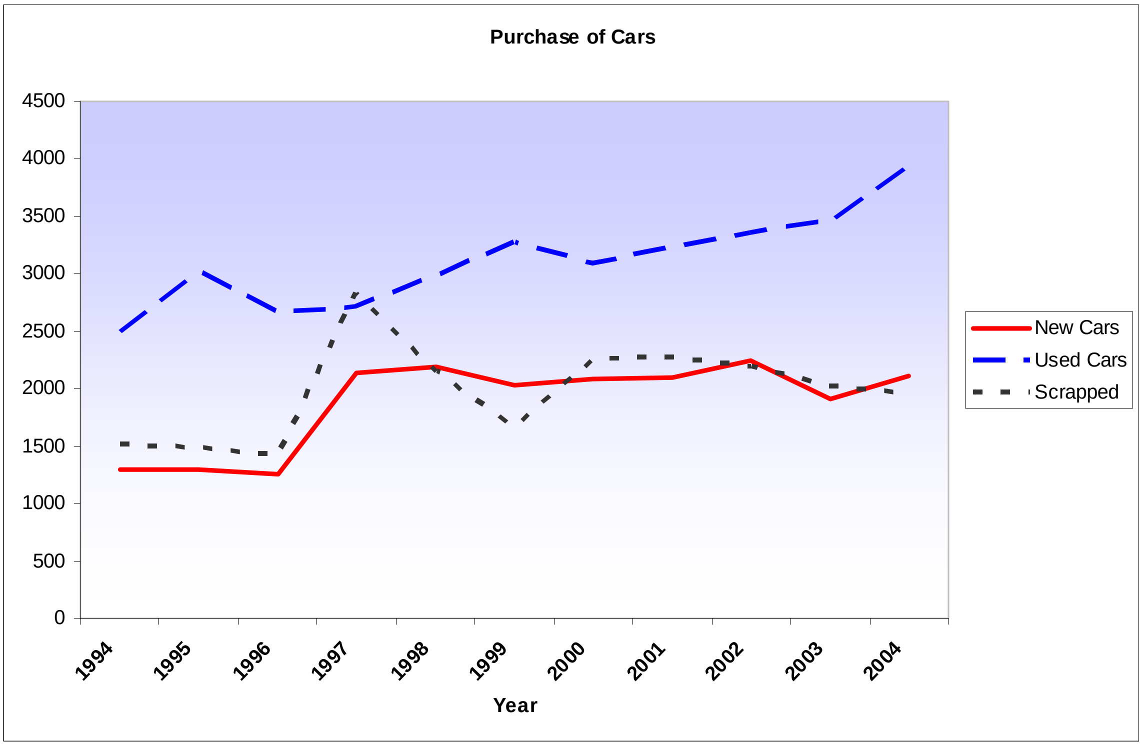


Figure 1 – Purchase of New and Used Cars

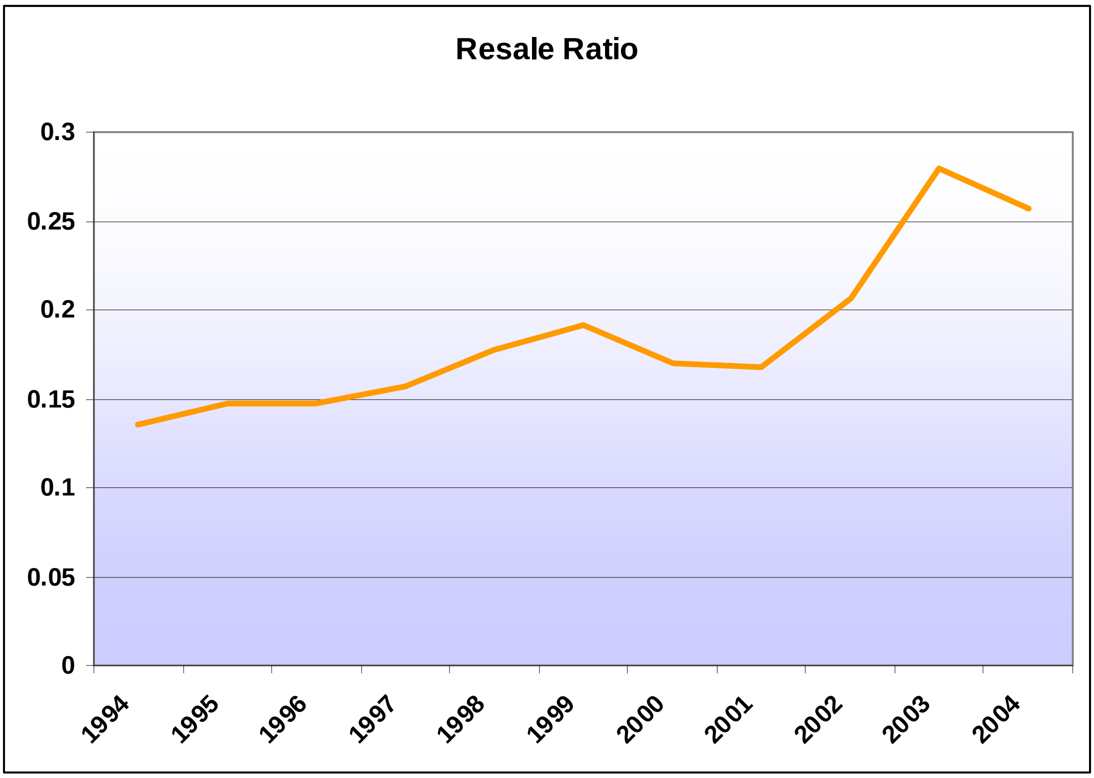
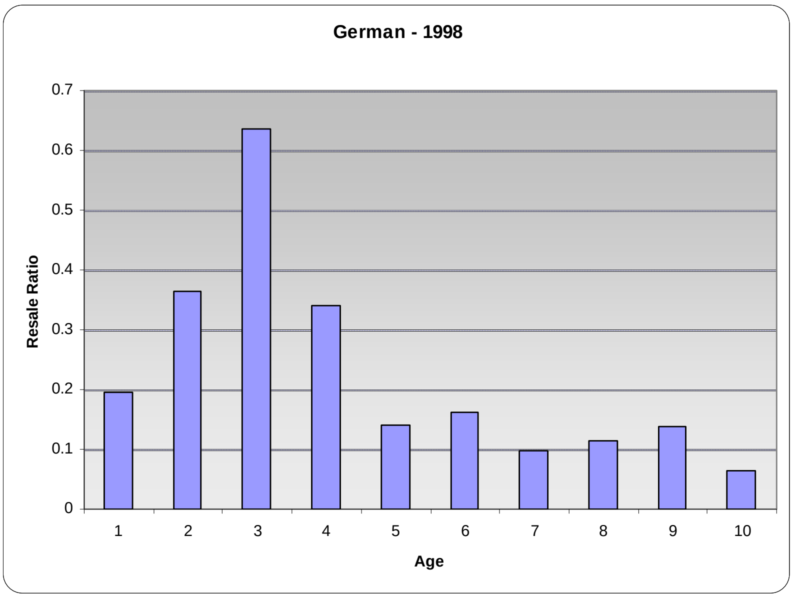
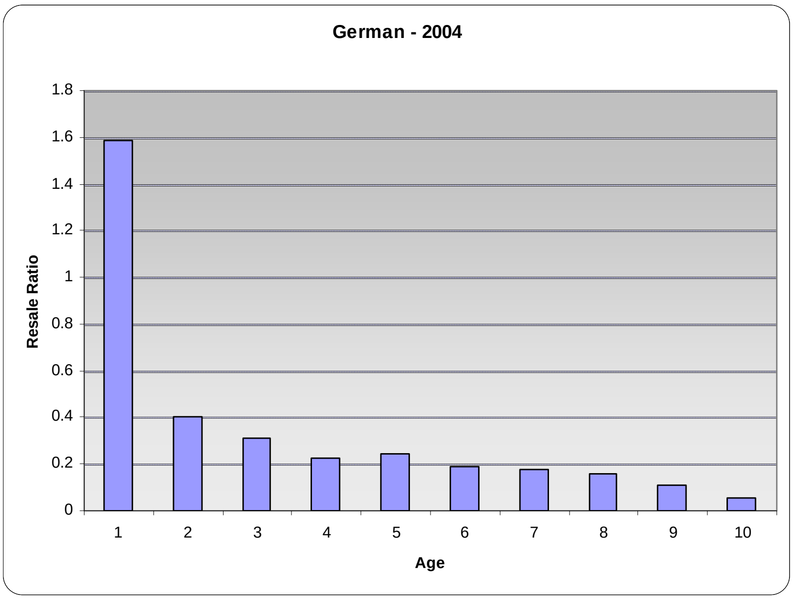
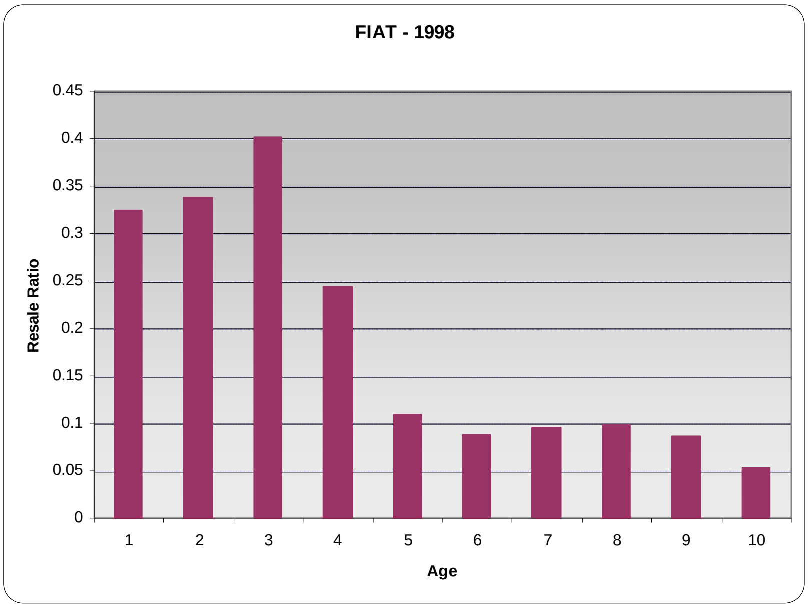


Figure 2 – Resale Ratio


German - 1998
Resale Ratio
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1 2 3 4 5 6 7 8 9 10
Age


German - 2004
Resale Ratio
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1 2 3 4 5 6 7 8 9 10
Age



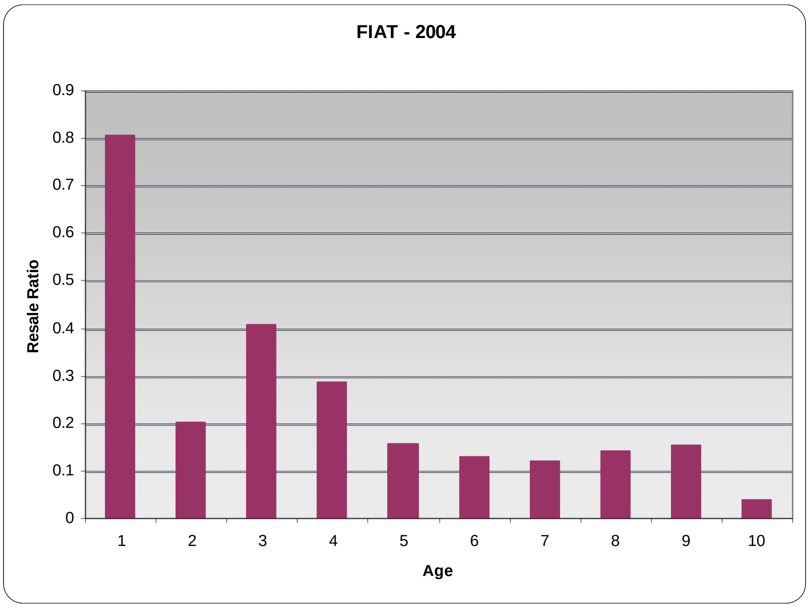


Figure 3 - Resale rates for different car types

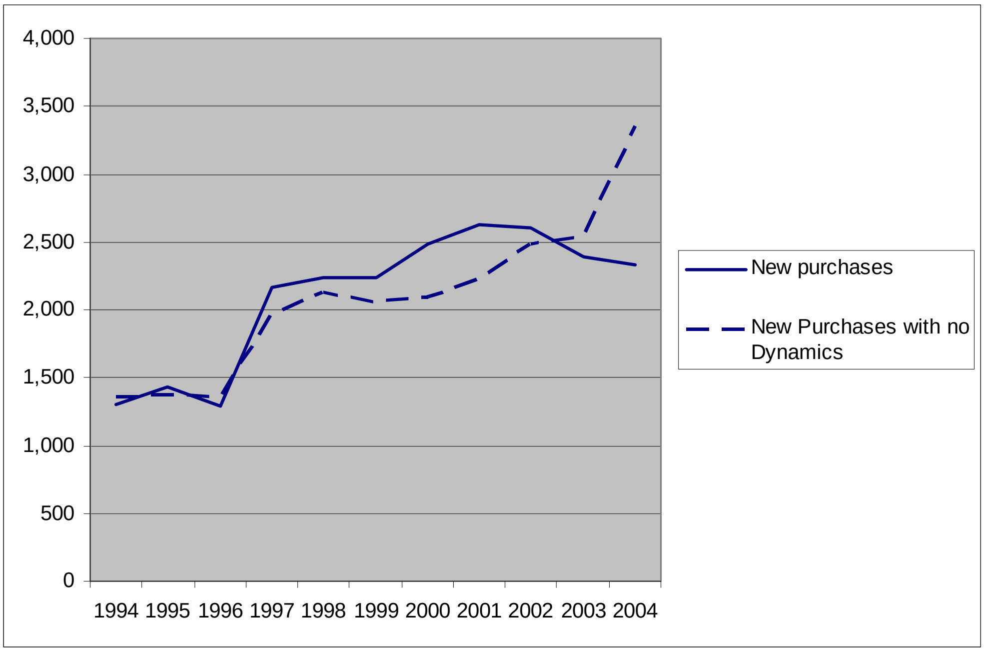


Figure 4: Simulation new purchases

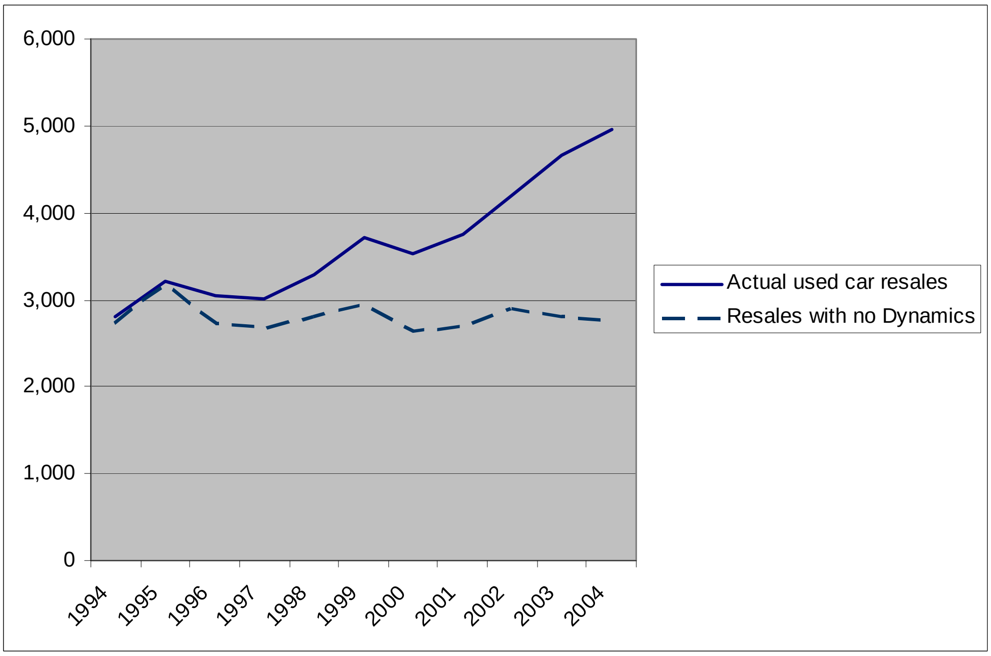


Figure 5: Simulation used car resales

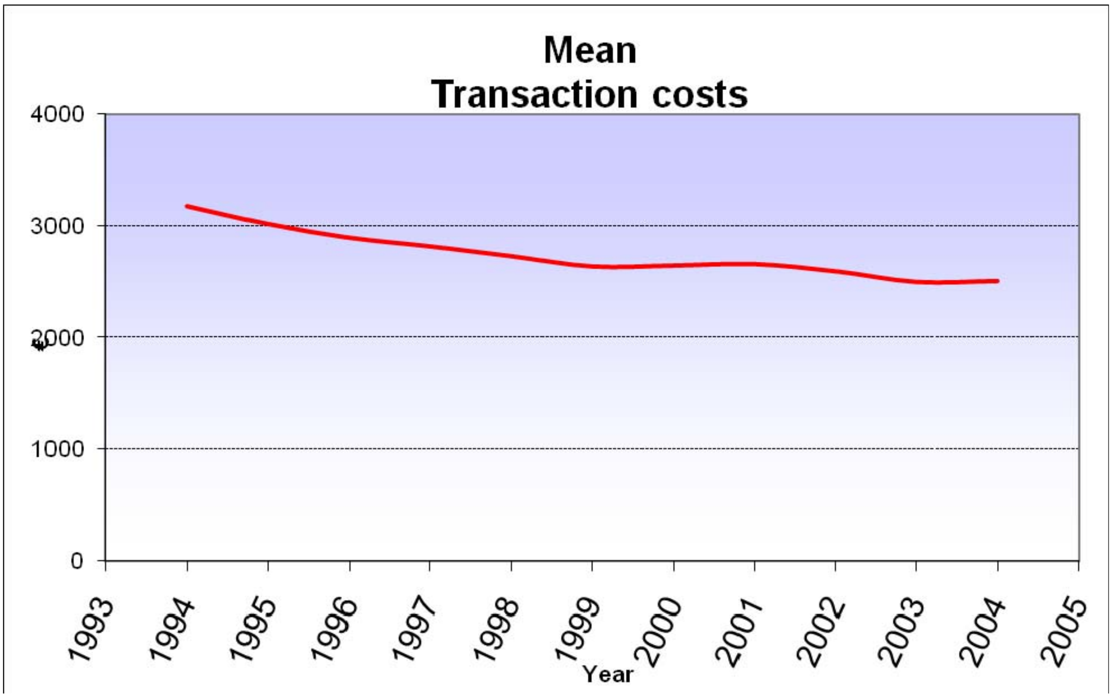


Figure 6 – Mean Transaction Costs over Time

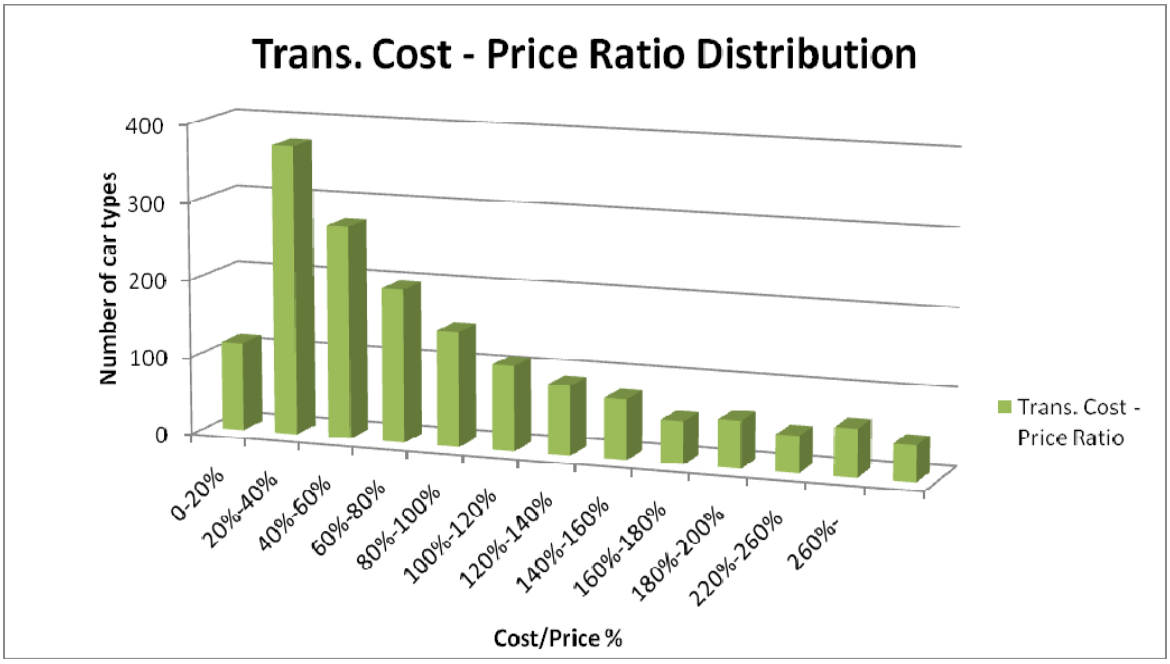


Figure 8 – Transaction Costs/Price Ratio

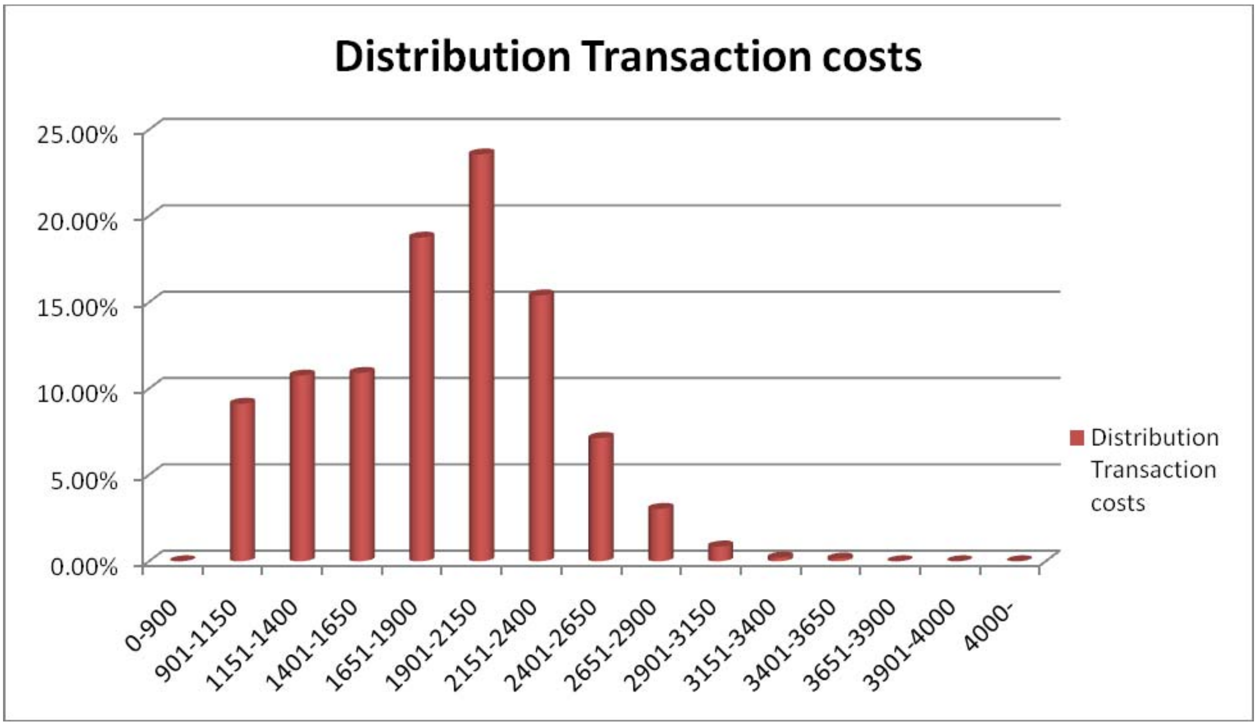


Figure 7 – Transaction Costs Distribution

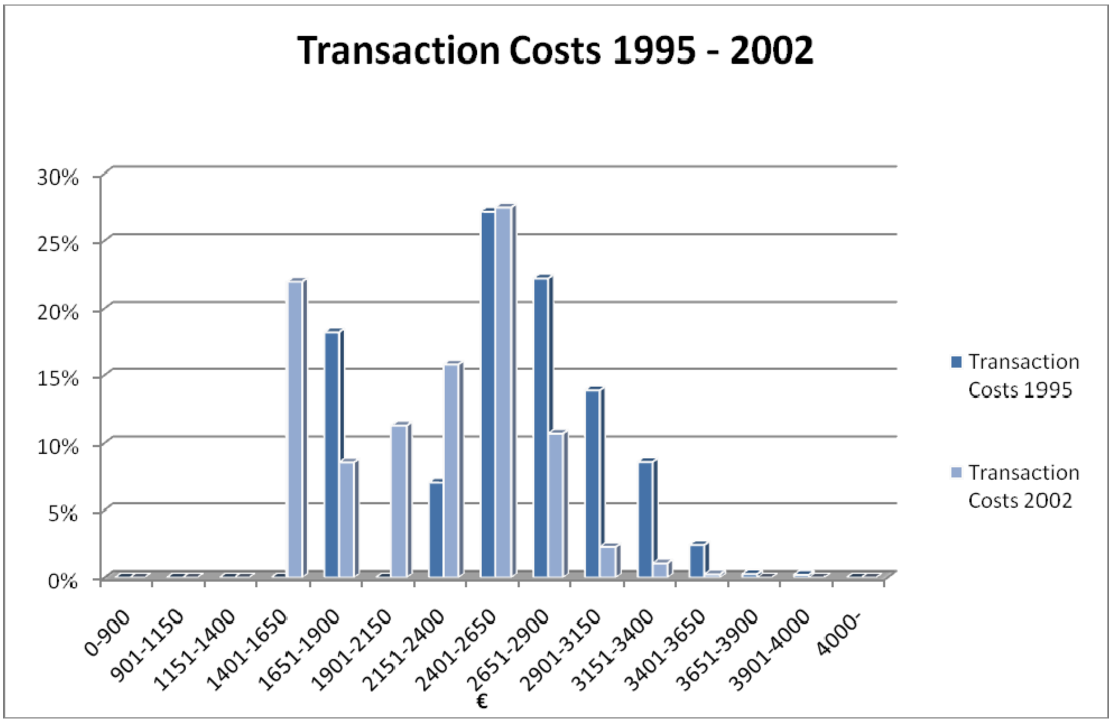


Figure 9 – Transaction Costs Distribution

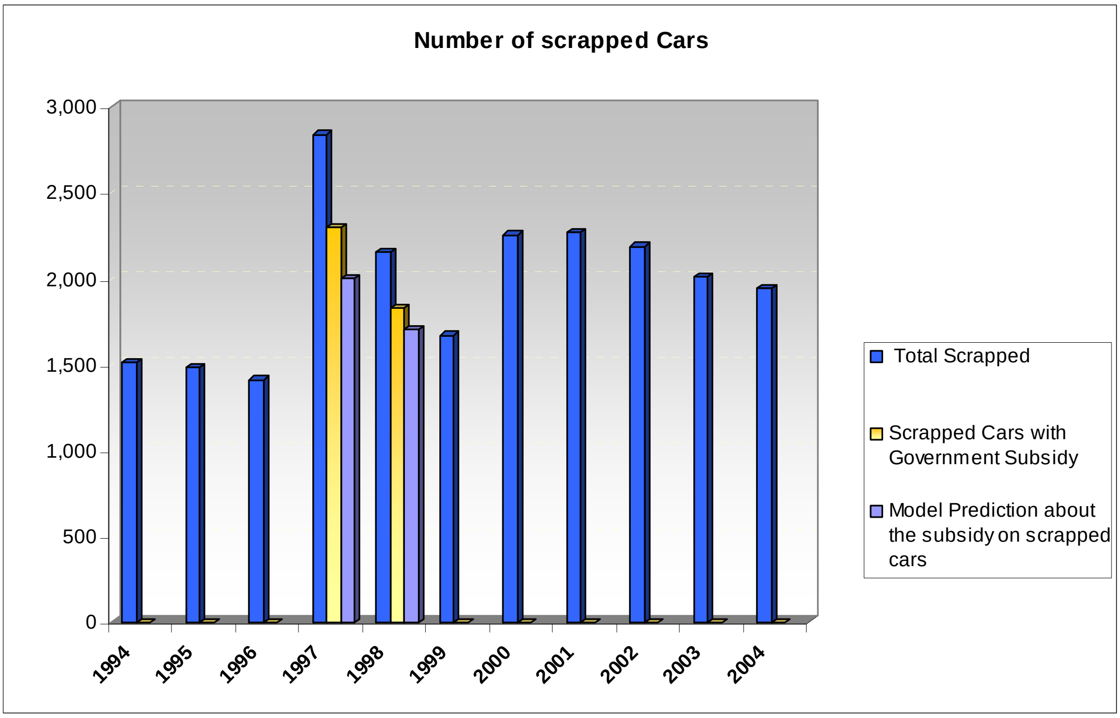


Table 10: Effect of Scrappage program

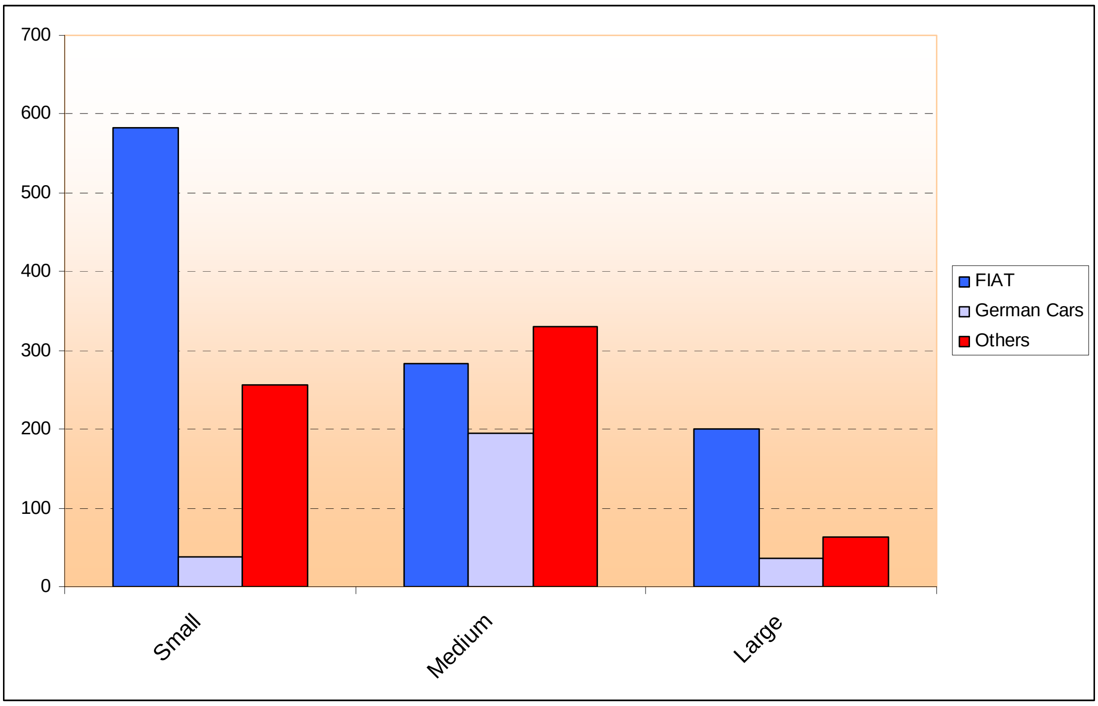


Figure 11 – Predicted sales of new cars