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Durable-Goods Oligopoly with Secondary Markets: the Case of Automobiles*

Susanna Esteban
Department of Economics
The Pennsylvania State University

Matthew Shum
Department of Economics
Johns Hopkins University

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Abstract

We study the effects of durability and secondary markets on equilibrium firm behavior in the car market. In this setting, the existence of secondary markets causes forward-looking firms to internalize the effect that their current production decisions have on their current and future profits. We construct a dynamic oligopoly model of a differentiated product market to understand the equilibrium production dynamics which arise from the durability of the goods and their active trade in secondary markets. We derive estimates of the model parameters using data from the automobile industry over a twenty-year period.

The quality rankings across car models implied by our estimates correspond largely to market perceptions. Results from counterfactual experiments suggest that durability may be a particularly desirable car feature for high-quality car producers since, by overproducing today, they can exploit durability and the existence of a secondary market to potentially reduce their lower-quality competitors' future production and future profits: planned obsolescence appears to be a more beneficial strategy for lower-end than higher-end producers.

1 Introduction

In many durable goods industries, used products are traded in decentralized secondary markets which are not directly controlled by the producers of new goods: the automobile industry is perhaps the most prominent example. In this paper we seek to understand the effects of durability and secondary markets on equilibrium behavior in this industry. In the context of a dynamic equilibrium model, we quantify explicitly how product durability and trade in secondary markets affects equilibrium producer behavior in the automobile market.

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The durability of cars and the existence of a secondary market have important competitive implications for new car producers.[1] Obviously, the secondary market introduces, in the form of used cars, a large number of (imperfect) substitutes to the new cars produced each period, limiting the market power of each producer. However, this detrimental effect on firms' market power is mitigated by the ability of consumers to trade cars in a secondary market, which introduces an additional component — the resale value — to consumers' valuations of new cars. New cars become (in part) investment assets, and this investment motive raises consumers' willingness-to-pay for new cars.

Furthermore, rational firms recognize that current production reaches the secondary market in the future and, by lowering prices in those markets, erodes both present as well as future profits. A durable goods monopolist fully internalizes this effect by curtailing current production. In a durable goods oligopoly, however, each producer internalizes only the effect this has on its own future profits, but not the detrimental effect it has on its rivals' future profits. Indeed, each oligopolistic producer derives an indirect benefit from increases in current production if this causes its rivals to lower their future production levels; in equilibrium, therefore, a firm may choose to overproduce today if these indirect benefits outweigh the costs of more vigorous competition from the secondary market tomorrow.

In short, durability and the existence of secondary markets imply that each firm's current profits depend not only on its own current, past and future production, but also on the current, past and future production of all its rivals. The interaction of all these effects makes for a rich dynamic game, and the goal of this paper is to examine the equilibrium dynamics of this game within the context of the automobile industry.

We proceed in several steps. First, we construct a dynamic oligopoly model of a differentiated product market to understand the equilibrium production dynamics which arise from the durability of the goods and their active trade in secondary markets. Second, we use data from the automobile market to estimate a tractable linear-quadratic version of the model. To our knowledge, this paper is the first empirical study of the car market within the framework of an equilibrium dynamic oligopoly model which recognizes the intertemporal linkages resulting from durability and trade in secondary markets. The quality rankings across car models implied by our estimates correspond largely to market perceptions, and our marginal cost estimates are consistent with the intuition that higher-quality cars are costlier to produce, while cars which depreciate faster are less costly to produce.

Finally, we use our estimated model parameters to consider several counterfactual experiments which shed further light on the dynamic effects of durability and secondary markets in this market. One important insight from these experiments is that the strategic use of secondary markets is more beneficial for higher-end than lower-end producers. By producing more today, higher-end producers intensify the future competition at the lower end of the market which, in our Cournot model, leads

[1] The Alcoa antitrust case inspired much academic interest in a similar question: the competitive implications of a primary market and a recycling industry where used aluminum can be reprocessed; see, for example, Gaskins (1974).

the low-end producers to reduce their future production. However, low-end producers cannot affect their high-end rivals in the same way, and the benefits they would derive from increasing production should be smaller accordingly. However, this effect is asymmetric: since low-end producers cannot affect their high-end rivals in the same way, they may prefer to make their cars less durable in order to reduce competition with their past production in the secondary market. Perhaps this explains the absence of durable cars at the lower-end, and nondurable cars at the higher-end, of the car market.

1.1 Background and existing literature

To our knowledge, this paper contains the first empirical study of the car market which accommodates the equilibrium production dynamics arising from car durability and active secondary markets. Empirically addressing the equilibrium effects of durability in a durable goods oligopoly is a challenging task: since durable goods markets are characterized by both forward-looking consumers as well as producers, it is generally difficult to describe a dynamic equilibrium in such a market. For example, forward-looking consumers base their current purchase decisions on their beliefs regarding future prices and/or quantities; however, a consistency requirement (such as rational expectations) implies that these beliefs must indeed be consistent with the firms' actual pricing and/or production decisions in equilibrium. Symmetrically, firms' pricing and production decisions must be profit-maximizing best-responses, given consumers' beliefs.

In this paper, we overcome these challenges by constructing a dynamic equilibrium model of the car market in which tractability and flexibility is provided by its linear-quadratic structure.[2] Our model captures four key characteristics of the car industry: *(i)* oligopolistic time-consistent automobile producers; *(ii)* an active, decentralized secondary market;[3] *(iii)* differentiated products; and *(iv)* depreciation schedules which differ across the competing car models.

Since the seminal work of Coase (1972), there has been a large theoretical literature analyzing how durability erodes market power for a monopoly producer. Coase conjectured that a monopoly producer of an infinitely-durable good may lose all of its market power due to its inability to commit to low levels of future production.[4] Subsequent work (eg. Stokey (1981), Gul, Sonnenschein, and Wilson (1986), and Ausubel and Deneckere (1989)) confirmed Coase's conjecture as an equilibrium limiting result in models where the time lag between the monopolist's price offers shrinks to zero.[5]

[2]See Kydland (1975) for a description of discrete-time linear-quadratic dynamic games, and Judd (1996) for an application of linear-quadratic models to a dynamic oligopoly setting where firms set both prices and quantities. Kahn (1986) analyzes the effects of increasing costs in an infinitely-durable goods monopoly framework and applies a linear-quadratic structure.

[3]Beginning with Akerlof (1970), one strand of the literature on secondary markets has focused at informational issues; recent work by Hendel and Lizzeri (1999a) consider a two-period durable goods market, and House and Leahy (2000) extend this framework to a longer time horizon. Bond (1982) tests for the presence of lemons in the truck market. Consumers and firms in our model act in a symmetric information environment, so we abstract away from adverse selection issues.

[4]See Bulow (1982) for a treatment of the durable-goods monopolist problem within a two-period model.

[5]However, Ausubel and Deneckere (1989) also prove a Folk Theorem for the limiting durable-goods monopoly game, and show that the Coase outcome is but one of a continuum of subgame-perfect equilibria for this game, which also includes an equilibrium in which the producer obtains profits arbitrarily close to the full-commitment monopoly

While these results have all been formulated in the monopoly context, we use our estimates to simulate counterfactual experiments which illustrate how oligopolistic firms would change their production behavior if they were able to commit to future production paths. These experiments suggest that the ability to commit would raise firms' profits, thus supporting Coase's conjecture. In the monopoly setting which has been the focus of most of the Coase Conjecture literature, these higher profits can only be achieved by decreases in future production. In an oligopolistic context, however, we find that some firms would obtain higher profit levels by *increasing* their equilibrium production levels.

In the presence of Coasian commitment problems, a secondary market may sharpen firms' incentives to hold back production because, if used cars are substitutes for new cars, any overproduction today will lead to lower used car prices (and therefore lower new car sales) in the future.[6] However, secondary markets do not completely mitigate commitment problems, since producers would like to commit to low future production levels in order to increase future resale values and, thereby, raise consumers' willingness-to-pay for new cars today. Bulow (1986) shows that, generally, a monopolist would try to reduce this commitment problem by planned obsolescence: that is, by reducing the durability of its product.[7] In a quantity-setting oligopoly, however, each producer may have a countervailing incentive to increase durability, in order to reduce its rivals' future production.

While we do not address directly the issue of durability choice in this paper, we use our estimates to simulate counterfactual experiments which gauge how the profitability of obsolescence varies across firms. We find that, with vertically-differentiated durable goods, this countervailing incentive is stronger for firms producing higher-quality goods, since used variants of these goods substitute readily with the new goods produced by lower-quality firms. One striking implication of this finding is that, in vertically-differentiated durable-goods oligopolies, the profitability of planned obsolescence varies across firms at different ends of the quality spectrum.

The implications of durability and secondary markets on the dynamics of car demand have not been ignored in the existing literature. Berkovec (1985), Rust (1985a), and Stolyarov (2000) focus on dynamic consumer demand in a durable goods market with primary, secondary and scrappage market segments. Adda and Cooper (2000) employ the optimal decision rules from a dynamic discrete-choice model to explore the effects of scrappage subsidies on car demand, where cars are held until scrapped and, hence, are not actively traded in the secondary market. Finally, Eberly (1994) and Attanasio (2000) consider (S, s) models of automobile demand in which idiosyncratic shocks lead consumers to change their stock of cars. In all these papers, the focus is on the timing of consumer purchases, so that automobile prices are assumed to evolve exogenously, and firms'

profits.

[6]See Liang (1999) for an articulation of this idea for a monopolist. Furthermore, results for a homogeneous product durable goods oligopoly from Ausubel and Deneckere (1987) and Gul (1987) show that, somewhat paradoxically, oligopolistic competition also acts as a commitment device which allows firms to avoid the Coase outcome by strengthening incentives to collude. The strategies which sustain collusive equilibria fall outside the linear-quadratic framework which we focus on in this paper.

[7]The issue of planned obsolescence has sparked a large theoretical literature; see, for example, Swan (1985) and Rust (1985b).

automobile production decisions are not explicitly modeled.

Our emphasis on the equilibrium dynamics due to durability and secondary markets also distinguishes our work from existing market-level empirical studies of demand and supply in the automobile market. Bresnahan (1981), Berry, Levinsohn, and Pakes (1995), Goldberg (1995), and Petrin (1999) have employed static models to quantify the degree of market power and the welfare effects of new product introductions in the car industry.

Several papers have considered the empirical implications of durability and monopoly power in the automobile market. Ramey (1989) estimated a durable goods monopoly model to explain aggregate trends in car prices, and Porter and Sattler (1999) test empirical predictions on the volume of trade in secondary car markets using a durable-goods monopoly model with transactions costs. There have been fewer papers on durable goods oligopoly. Carlton and Gertner (1989) analyzed the effects of mergers among oligopolistic durable goods producers, and Esteban (2001) characterizes the equilibrium production dynamics in a durable-goods oligopoly with homogeneous products. What distinguishes our work is the focus on differentiation (in both quality as well as durability) among the car models produced by forward-looking oligopolistic rivals.

The paper proceeds as follows. In Section 2 we introduce the model, and derive the Markov Perfect Equilibrium of the dynamic game. Subsequently, we derive a linear-quadratic specification of this model which is convenient for the empirical work. In Section 3 we describe the data and discuss the empirical implementation of the model. In Section 4 we describe our estimation results and conduct different counterfactual experiments. We conclude in Section 5.

2 A Model of Durable Goods Oligopoly with Secondary Markets

We consider a dynamic quantity-setting game among oligopolistic producers of differentiated durable goods (in this case cars). On the demand side, we assume that consumers are forward looking, so that durability and secondary markets introduce dynamic investment considerations into their car consumption decisions. On the supply side, we assume that new car producers are quantity-setting oligopolists who recognize both the intertemporal effect of current production on future profits due to the secondary market as well as the dependence of current profits on past, present and expected future production.[8] For simplicity, we introduce the theoretical model in a deterministic context; later, when we describe the estimation procedure, we will introduce shocks which generate the additional randomness in the endogenous variables required for the econometric exercise.

Following Esteban (1999), we assume that the available cars are vertically differentiated. We refer to cars in their first period of life as *new* cars and, thereafter, as *used* cars. Throughout, we assume

[8] Several institutional features support a quantity-setting assumption. First, an implicit assumption of the Bertrand price-setting model is flexible capacity, and capacity does not generally appear easily adjustable in car production. Second, in the car market prices seem to adjust to clear the market at given quantity levels, as in the quantity-setting case. For example, rebates are a common way of adjusting new car prices to clear the inventories at the end of the model year. Finally, dealer behavior limits the manufacturers' ability to control prices.

that used cars are transacted in competitive and decentralized secondary markets, so that new car producers can manipulate market outcomes in the secondary market only indirectly, through their production of new cars.

Each period, N firms produce new cars. We let $\mathcal{N}$ denote the set of firms, where $N \equiv |\mathcal{N}|$. Each firm $j \in \mathcal{N}$ produces L_j distinct models, where $L_j \equiv |\mathcal{L}_j|$ and $\mathcal{L}_j$ is the set of all models produced by this firm. Then, $\mathcal{L} \equiv \cup_j \mathcal{L}_j$ is the set of all models produced by all firms and $L \equiv |\mathcal{L}|$ is their total number. We index models by $i = 1, \dots, L$.

New cars differ in quality and durability. For each model $i \in \mathcal{L}$, we let $q_{i,h}$ denote its quality at age h, where $h = 1, \dots, T_i$ indexes its age and $T_i < \infty$ denotes the number of periods it lasts. Then, each car (new or used) is completely described by the pair (i, h), and the set of all distinct cars transacted is given by $\mathcal{K} \equiv \{(i,h)|i \in \mathcal{L}, h = 1, \dots, T_i\}$ and $K \equiv |\mathcal{K}|$ is their total number.

Next, we define a mapping $\omega : \mathcal{K} \mapsto \{1, \dots, K\}$ which ranks cars from highest to lowest quality as follows

$$\forall (i,h) \neq (i',h') \in \mathcal{K},\ q_{i,h} > q_{i',h'} \Rightarrow \omega(i,h) < \omega(i',h').$$

Hence, a ranking of 1 denotes the highest-quality car, and a ranking of K the lowest quality. Given this ranking, we define a quality ladder as follows.

Definition 1 *A vector $\boldsymbol{\alpha} = [\alpha_1,\ \alpha_2,\ \dots,\ \alpha_K, 0]'$ is a **quality ladder** representing the quality structure of this problem if $\alpha_k \equiv \{q_{i,h}|k = \omega(i,h)\}$.*

To facilitate the subsequent exposition, it is convenient to define a depreciation schedule for each car model as follows. Given a quality ladder $\boldsymbol{\alpha}$, we define a second mapping $v : \{1, \dots, K\} \mapsto \{1, \dots, K\}$ which tracks the position that a car currently in position k occupies after one period of depreciation. Then, $v(\omega(i,1)) = \omega(i,2)$ and, more generally,

$$v^{h-1}(\omega(i,1)) \equiv \underbrace{v(v(\dots v(}_{h-1 \text{ times}}\omega(i,1)))) = \omega(i,h), \quad \text{for } h = 2, \dots, T_i - 1.$$

Cars which die (i.e., all cars (i,h) where $h > T_i$) are given a ranking of $K+1$ (since $\alpha_{K+1} = 0$), so that $v^{T_i}(\omega(i,1)) = K+1$, for all $i \in \mathcal{L}$, and $v(K+1) = K+1$.

Finally, we let $\eta(i) \equiv \omega(i,1)$, for all $i \in \mathcal{L}$, denote the position that a model i car takes in the quality ladder when new. Then, we represent the depreciation schedule of a model i car by the sequence

$$\eta(i), v(\eta(i)), v^2(\eta(i)), \dots v^{T_i}(\eta(i)),$$

which indicates the positions in the ladder occupied successively by a model i car. We now turn to the demand side of our model.

2.1 Demand in a vertically differentiated market

2.1.1 The consumer's problem

Our consumer population is a continuum of infinitely-lived agents in which population heterogeneity in consumers' taste for quality generates demand for each type of car. In each period t, each consumer determines her optimal consumption choice among the K available cars and the option of not consuming a car at all (which we index $K+1$), to maximize her discounted utility function.[9]

For tractability, we assume that consumers face no transactions costs in any primary or secondary market.[10] In deriving consumers' optimal car choice rules, we also assume that they possess perfect foresight about the sequences of future prices across all car markets $p^k_{t+\tau}$ for $k = 1, \dots, K$, and $\tau = 1, \dots, \infty$.[11] Heterogeneity among consumers is parameterized by a scalar type $\theta \in [0, \bar{\theta}]$ (where $\bar{\theta} < \infty$), and is distributed in the population according to the cumulative distribution $F(\cdot)$. The population has size M.

Then, a consumer of type θ chooses a sequence of car choices to maximize her discounted lifetime utility[12]

$$U^\theta \equiv \sum_{t=1}^{\infty} \delta^{t-1} U^\theta_t. \tag{1}$$

Her period t utility flow is assumed to be quasilinear in income and given by

$$U^\theta_t \equiv \alpha_k \theta + m^\theta_t - p^k_t, \tag{2}$$

where δ denotes the discount factor common across all consumers and firms, θ measures this consumer's willingness-to-pay for quality, and m^θ_t denotes consumer θ's income at the beginning of period t.[13]

As is well known, the assumptions of quasilinearity and no transaction costs imply that a consumer's optimal consumption decision in any period does not depend on her past and future choices, since her decisions are independent of income. Then, it is easy to verify that consumer θ's optimal car

[9]In the empirical implementation section, we will interpret the nonpurchase choice as the consumption of an outside good.

[10]Consumer transactions costs mainly affect the *timing* dimension of consumers' car purchases. Since we focus on equilibrium producer behavior rather than consumer demand patterns, this assumption is not particularly restrictive for our purposes.

[11]This assumption is natural along the (pure strategy) equilibrium path of the dynamic model in the absence of shocks. When shocks are present, however, perfect foresight is no longer a palatable assumption, but the derivations in this model still obtain under the weaker assumption of rational expectations for the case where $F(\theta)$ is uniform. See footnote 27 for a more detailed exposition.

[12]Her discounted lifetime utility is deterministic for any sequence of cars that she chooses. This arises from the perfect foresight assumption.

[13]Since we normalize α_{K+1} to zero, we set $p^{K+1}_t = 0$, $\forall t$, accordingly. This implies that a car that dies in period t has zero resale value. In our empirical application, we adopt an alternative assumption that when cars die, consumers receive some positive, but exogenously given, scrappage value. In all cases, however, the scrappage sector is not endogenized. This extension is described fully in Appendix Section B.1.

choice in period t is determined by simply comparing the *utility gains*

$$UG_t^k(\theta) \equiv \alpha_k\theta - p_t^k + \delta p_{t+1}^{v(k)} \tag{3}$$

across all choices $k = 1, \ldots, K+1$. Each utility gain is just the difference of $\alpha_k\theta$, the per-period flow of services that consumer θ obtains from car k, and $(p_t^k - \delta p_{t+1}^{v(k)})$, the implicit rental price paid for those services, where $\delta p_{t+1}^{v(k)}$ is the discounted resale price in tomorrow's secondary market. In every period, therefore, the optimal decision rule dictates that consumer θ chooses the car $k = 1, \ldots, K+1$ which maximizes the utility gain given in equation (3). We provide a formal proof of this result in Appendix A.[14]

2.1.2 *Deriving the demand functions*

The consumer preferences specified above imply that competing cars are *vertically differentiated*, in the sense that if all cars were priced identically, all consumers would choose the highest quality car.[15] Following the literature on oligopoly models of vertically-differentiated product markets (eg. Prescott and Visscher (1977), Bresnahan (1981) and Berry (1994)), we derive the period t demand functions as follows. Given prices p_t^k, $p_{t+1}^{v(k)}$ for $k = 1, \ldots, K$ and quality levels $\alpha_1, \ldots, \alpha_K$, and subject to regularity conditions ensuring that each car model has positive demand (fully discussed at the end of this section), we find K cutoff values, $\tilde{\theta}_t^1, \ldots, \tilde{\theta}_t^K$, such that

$$\bar{\theta} \geq \tilde{\theta}_t^1 \geq \tilde{\theta}_t^2 \geq \tilde{\theta}_t^3 \geq \ldots \geq \tilde{\theta}_t^K \geq 0, \tag{4}$$

and all consumers with preference parameter $\theta \in [\tilde{\theta}_t^1, \bar{\theta}]$ consume car 1, all consumers with preference parameter $\theta \in [\tilde{\theta}_t^2, \tilde{\theta}_t^1]$ consume car 2, etc. Finally, all consumers with preference parameter $\theta \in [0, \tilde{\theta}_t^K]$ do not consume a car. These cutoff values solve the indifference conditions

$$\begin{aligned} \alpha_k\tilde{\theta}_t^k - p_t^k + \delta p_{t+1}^{v(k)} = &\quad \alpha_{k+1}\tilde{\theta}_t^k - p_t^{k+1} + \delta p_{t+1}^{v(k+1)}, \quad \text{for } k = 1, \ldots, K-1, \\ \alpha_K\tilde{\theta}_t^k - p_t^k = &\quad 0, \qquad\qquad\qquad\qquad\qquad \text{for } k = K. \end{aligned} \tag{5}$$

Let x_t^k denote the demand for car k in period t, given by the measure of consumers who receive a

[14] This simplification of the consumers' problem relies on the assumption of no transaction costs: if (for example) we allowed for transaction costs in selling a used car, then a consumer's utility gain from choosing car $v(k)$ in period t would depend on whether she owned car $v(k)$ at the beginning of period t (that is, whether she chose car k in period $t-1$). As a result, the consumer's utility maximization problem would be state dependent. See Anderson and Ginsburgh (1994), Porter and Sattler (1999) and Stolyarov (2000) for analyses of a durable goods market with transactions costs.

[15] See Prescott and Visscher (1977) for a static differentiated-product oligopoly model, and Bresnahan (1981) for its application to the automobile industry. While our scalar heterogeneity specification echoes the demand specification in these papers, much of the more recent empirical literature on the car industry (Berry, Levinsohn, and Pakes (1995), for example) has focused on modeling heterogeneity in consumer preferences by allowing for multiple dimensions of consumer heterogeneity. However, there are difficult conceptual as well as computational issues involved in extending models with multi-dimensional heterogeneity in preferences to a dynamic equilibrium framework. See Berry and Pakes (1999) for some discussion of the challenges in computing and estimating multi-dimensional vertical differentiation models.

maximal utility gain from car k:

$$x_t^k = \begin{cases} M(1 - F(\tilde{\theta}_t^k)), & \text{for } k = 1, \\ M(F(\tilde{\theta}_t^{k-1}) - F(\tilde{\theta}_t^k)), & \text{for } k = 2, \ldots, K. \end{cases} \tag{6}$$

Substituting these demand functions recursively in equation (6), we write the K cutoff values as

$$\tilde{\theta}_t^k = F^{-1}\left(1 - \frac{1}{M}\sum_{r=1}^{k} x_t^r\right), \quad \text{for } k = 1, \ldots, K. \tag{7}$$

Subsequently, substituting these expressions for the cutoff values into the indifference conditions given in equation (5), and imposing a natural non-negativity constraint on market prices, we obtain the inverse demand functions for each of the cars sold. In particular, a new car model $i \in \mathcal{L}$ with history $\eta(i), \upsilon(\eta(i)), \ldots, \upsilon^{T_i}(\eta(i))$ has inverse demand function

$$p_t^{\eta(i)} = \max\left\{\left(\alpha_{\eta(i)} - \alpha_{\eta(i)+1}\right) F^{-1}\left(1 - \frac{1}{M}\sum_{r=1}^{\eta(i)} x_t^r\right) + \delta p_{t+1}^{\upsilon(\eta(i))} + p_t^{\eta(i)+1} - \delta p_{t+1}^{\upsilon(\eta(i)+1)}, 0\right\}, \tag{8}$$

where the prices $p_{t+1}^{\upsilon(\eta(i))}, p_t^{\eta(i)+1}$ and $p_{t+1}^{\upsilon(\eta(i)+1)}$ are derived in analogous fashion.

The non-negativity constraint on the inverse demand functions given by equation (8) implies that the primary and secondary markets can be in excess supply, in which case the constraint binds and the price equals zero. In order to maintain the tractability of the model, however, we assume that the non-negativity constraints never bind in any market.[16] Under this assumption, we substitute prices recursively into equation (8) and obtain the inverse demand function for new model $i \in \mathcal{L}$ as

$$\begin{aligned} p_t^{\eta(i)} = &\sum_{k=\eta(i)}^{K} (\alpha_k - \alpha_{k+1}) F^{-1}\left(1 - \frac{1}{M}\sum_{r=1}^{k} x_t^r\right) \\ &+ \sum_{h=1}^{T_i-1} \delta^h \left(\sum_{k=\upsilon^h(\eta(i))}^{K} (\alpha_k - \alpha_{k+1}) F^{-1}\left(1 - \frac{1}{M}\sum_{r=1}^{k} x_{t+h}^r\right)\right). \end{aligned} \tag{9}$$

We end this section with a discussion of the regularity conditions on prices $p_t^k, p_{t+1}^{\upsilon(k)}$ for $k = 1, \ldots, K$, and qualities $\alpha_1, \ldots, \alpha_K$ which are required to obtain period t demand functions in the cutoff manner described above. Essentially, these regularity conditions must ensure that the cutoff values $\tilde{\theta}_t^1, \ldots, \tilde{\theta}_t^K$ are non-increasing in the quality of the good k, so that the demand for each car is positive.

[16]For some parameter values, this assumption rules out the possibility that, in equilibrium, firms overproduce strategically in order to send some markets into excess supply. Esteban (2001) studies this issue for the case of a monopolist producer and shows that, in equilibrium, the secondary market will never be in excess supply for any depreciation of cars. For more general vertical differentiation structures, however, the result does not necessarily generalize.

Therefore, for every car $k = 2, \ldots, K$, and every period t, the following inequality must be satisfied

$$\begin{aligned}
&\frac{(p_t^{k-1} - \delta p_{t+1}^{\upsilon(k-1)}) - (p_t^k - \delta p_{t+1}^{\upsilon(k)})}{\alpha_{k-1} - \alpha_k} \\
\geq &\frac{(p_t^k - \delta p_{t+1}^{\upsilon(k)}) - (p_t^{k+1} - \delta p_{t+1}^{\upsilon(k+1)})}{\alpha_k - \alpha_{k+1}} \\
\geq &\frac{(p_t^{k+1} - \delta p_{t+1}^{\upsilon(k+1)}) - (p_t^{k+2} - \delta p_{t+1}^{\upsilon(k+2)})}{\alpha_{k+1} - \alpha_{k+2}} \\
\geq &0.
\end{aligned} \tag{10}$$

A necessary (but not sufficient) condition for these inequalities to be satisfied is that the implicit rental prices follow the same order as their positions in the quality ladder, i.e., for a given quality ladder $\alpha_1 \geq \cdots \geq \alpha_K$, the implicit rental prices are ordered

$$p_t^1 - \delta p_{t+1}^{\upsilon(1)} \geq p_t^2 - \delta p_{t+1}^{\upsilon(2)} \geq \cdots \geq p_t^K - \delta p_{t+1}^{\upsilon(K)}, \tag{11}$$

for all periods t. As we discuss later, the requirement that these inequalities hold across all time periods raises difficulties for the empirical implementation.

2.2 The producers' dynamic problem

Having derived the inverse-demand functions for each car transacted, we now turn to the supply side and analyze the dynamic optimization problem faced by producers. The assumption that no market will be in excess supply (i.e., that the non-negativity constraint in equation (8) does not bind) implies that the quantity demanded will equal the quantity supplied in all markets. Consequently, for each car model $i \in \mathcal{L}$, volumes in the secondary market evolve according to[17]

$$x_{t+h-1}^{\upsilon^{h-1}(\eta(i))} \equiv x_t^{\eta(i)}, \quad \text{for } h = 2, \ldots, T_i. \tag{12}$$

That is, the current production of model i, $x_t^{\eta(i)}$, becomes the supply in secondary market $\upsilon(\eta(i))$ during period $t+1$, and becomes the supply in secondary market $\upsilon^2(\eta(i))$ during period $t+2$, and so on.

Let $\boldsymbol{y}_t$ denote the vector of all cars-in-use (both new and used) in period t, defined as[18]

$$\boldsymbol{y}_t \equiv [1, x_t^1, \ldots, x_t^K]'. \tag{13}$$

Furthermore, $\boldsymbol{d}_t$ denotes the L-dimensional vector of all new cars $(L \times 1)$ produced in period t as

$$\boldsymbol{d}_t \equiv \left[x_t^{\eta(1)}, x_t^{\eta(2)}, \ldots, x_t^{\eta(L)}\right]'.$$

[17] Implicit in this equation is that durability is deterministic, in the sense that there is no exogenous decrease in car stocks due to, for example, accidents. However, our model easily accommodates these decreases in stocks, so that $x_{t+h-1}^{\upsilon^h(\eta(i))} \equiv \zeta_{i,h} x_t^{\eta(i)}$, where the probability of an accident is $\zeta_{i,h} \in [0,1]$.

[18] As is standard in the matrix form formulation of linear-quadratic problems (and anticipating the linear-quadratic specification of this model), we set the first entry of $\boldsymbol{y}_t$ equal to 1 identically across all t.

Given these definitions, the law of motion of the cars-in-use vector $\boldsymbol{y}_t$ is

$$\boldsymbol{y}_t = \boldsymbol{A}\boldsymbol{y}_{t-1} + \boldsymbol{B}\boldsymbol{d}_t, \tag{14}$$

where $\boldsymbol{B}$ and $\boldsymbol{A}$ are matrices which, respectively, place new car models in the quality ladder and shift cars within the quality ladder as they age. Specifically, $\boldsymbol{B}$ is a $(K+1)\times L$ matrix with entries

$$B(k+1,i) \equiv \begin{cases} 1, & \text{if } \eta(i)=k \\ 0, & \text{otherwise} \end{cases}, \quad \text{for } i=1,\dots,L,\ k=1,\dots,K, \tag{15}$$

and $\boldsymbol{A}$ is a $(K+1)\times(K+1)$ matrix with entries[19]

$$A(k'+1,k+1) \equiv \begin{cases} 1, & \text{if } k'=k=0 \\ 1, & \text{if } v(k)=k' \\ 0, & \text{otherwise} \end{cases}, \quad \text{for } k,k'=1,\dots,K. \tag{16}$$

Next, we let $C_j(x_t^{\eta(i)};\forall i\in\mathcal{L}_j)$ denote the total cost of production for firm j. Then, we can write j's period t profit function as

$$\begin{aligned} \pi_t^j &= \sum_{i\in\mathcal{L}_j} p_t^{\eta(i)}\left(x_{t+\tau}^1,\dots,x_{t+\tau}^K;\tau=0,\dots,T_i-1\right)x_t^{\eta(i)} - C_j(x_t^{\eta(i)};\forall i\in\mathcal{L}_j) \\ &= \sum_{i\in\mathcal{L}_j} p_t^{\eta(i)}\left(\boldsymbol{y}_{t+\tau};\tau=0,\dots,T_i-1\right)x_t^{\eta(i)} - C_j(x_t^{\eta(i)};\forall i\in\mathcal{L}_j) \\ &\equiv \sum_{i\in\mathcal{L}_j} \Pi^i\left(\boldsymbol{y}_{t+\tau};\tau=0,\dots,T_i-1\right), \end{aligned} \tag{17}$$

where $p_t^{\eta(i)}(x_{t+\tau}^1,\dots,x_{t+\tau}^K;\tau=0,\dots,T_i-1)$ denotes the inverse demand function in equation (9).

From the construction of π_t^j in equation (17), we see that firm j's profits in period t depend not only on its own current, past and future production, but also on the current, past and future production of all its rivals. The latter dependence arises only in a durable-goods oligopoly. In this dynamic setting, therefore, firms' production strategies at a given period t can become unwieldy because they can depend on the entire production history of all firms prior to period t. An appealing and natural assumption here is to allow firms' production choices today to depend only on cars produced in the past which still actively trade in secondary markets today.

This corresponds to a standard Markov assumption that firms's strategies only depend on past variables which affect current (period t) profits.[20] In our dynamic setting, these "payoff-relevant" variables are $\boldsymbol{A}\boldsymbol{y}_{t-1}$, the vector of the stock of cars produced prior to period t which are still actively traded in secondary markets.[21] Hence, we focus on production strategies of the form

$$x_t^{\eta(i)} = g_i(\boldsymbol{A}\boldsymbol{y}_{t-1}), \forall i\in\mathcal{L}_j,\ \forall j\in\mathcal{N}. \tag{18}$$

[19]Note that the first row and column of $\boldsymbol{A}$ is filled with a one, to be consistent with the first entry in the $\boldsymbol{y}_t$ vector.
[20]See Fudenberg and Tirole (1991), chap. 13, for a discussion.

[21]Note that the state vector cannot be $\boldsymbol{y}_{t-1}$, because this vector contains $x_{t-1}^{v^{T_i-1}(\eta(i))}$, the cars which have died between periods $t-1$ and period t, which cannot affect period t profits directly.

Then, for all periods, each firm $j \in \mathcal{N}$ chooses new car production $x_t^{\eta(i)}$, for all $i \in \mathcal{L}_j$, to maximize its period t-discounted profits anticipating the optimal future behavior of all producers of new cars by solving

$$\max_{x_t^{\eta(i)},\forall i\in\mathcal{L}_j} \sum_{\tau=1}^{\infty}\sum_{i\in\mathcal{L}_j} \delta^{\tau-1}\left[\Pi^i\left(\boldsymbol{y}_{t+\tau},\boldsymbol{y}_{t+\tau+1},\ldots,\boldsymbol{y}_{t+\tau+T_i-1}\right)\right], \tag{19}$$

subject to

$$\begin{array}{ll} \boldsymbol{y}_{t+\tau} & = \boldsymbol{A}\boldsymbol{y}_{t+\tau-1} + \boldsymbol{B}\boldsymbol{d}_{t+\tau} \\ x_{t+\tau}^{\eta(i)} & = g_i(\boldsymbol{A}\boldsymbol{y}_{t+\tau-1}) \end{array}, \quad \text{for } \tau = 1,\ldots,\infty. \tag{20}$$

Each firm's maximization problem can be represented by a dynamic programming problem with state variable $A\boldsymbol{y}_{t-1}$. Hence, for our dynamic durable-goods oligopoly game, a **Markov perfect equilibrium** specifies decision rules, $g_i(\cdot)$, for all $i \in \mathcal{L}_j$, and $j \in \mathcal{N}$, and value functions $V_j(\cdot)$, and $j \in \mathcal{N}$, such that these solve the dynamic programming problems given by the Bellman equation

$$V_j(\boldsymbol{A}\boldsymbol{y}_{t-1}) = \max_{x_t^{\eta(i)},\forall i\in\mathcal{L}_j} \sum_{i\in\mathcal{L}_j} \Pi^i(\boldsymbol{y}_t,\boldsymbol{y}_{t+1},\ldots,\boldsymbol{y}_{t+T_i-1}) + \delta V_j(\boldsymbol{A}\boldsymbol{y}_t), \tag{21}$$

where

$$\boldsymbol{y}_{t+h} = \boldsymbol{A}\boldsymbol{y}_{t+h-1} + \boldsymbol{B}g(\boldsymbol{A}\boldsymbol{y}_{t+h-1}), \quad \text{for } h = 1,\ldots,T_i, \tag{22}$$

and

$$x_t^{\eta(i)} = g_i(\boldsymbol{A}\boldsymbol{y}_{t-1}), \quad \text{for } i \in \mathcal{L}_j. \tag{23}$$

In this problem, dynamics arise because cars are durable, and current production trades in future secondary markets. The optimization problem in equations (21) to (23)) shows that forward-looking firms recognize this intertemporal linkage: each firm chooses its current production cognizant that it affects future profits through both future stocks in the secondary market, as well as the equilibrium production rules (23), whereby future production of all firms depends on current production.

In our differentiated-product oligopoly, however, the magnitude of these intertemporal effects also depends on differences in depreciation schedules between the competing car models: a firm producing a model which depreciates relatively quickly faces less intense competition from its past production and, hence, tends to produce more. Analogously, a firm producing a model which depreciates slowly tends to produce less.

Furthermore, the position of one producer's cars, relative to those of its competitors, in the quality ladder also affects its equilibrium production levels. Each producer indirectly benefits from increasing production if this decreases its rivals' future production. These benefits are largest for the high-end producers because, by producing more cars today, they intensify the future competition at the lower end of the market which, in our Cournot model, leads the low-end producers to reduce their future production. However, low-end producers cannot affect their high-end rivals in the same way, and the benefits they would derive from increasing production should be smaller accordingly.

Finally, we note that the production strategies $g_i(\cdot)$, for all $i \in \mathcal{L}$, that solve the dynamic programming problem in equation (21) are *time consistent*, in the sense that firms correctly anticipate their own future optimal behavior. Time-consistency is equivalent to the principle of optimality for dynamic programming problems. Generally, firms can obtain a higher discounted profit stream by committing to future production paths $\left\{x_{t+\tau}^{\eta(i)},\ \forall i \in \mathcal{L}_j\right\}_{\tau=0}^{\infty}$ that maximize

$$\max_{\left\{x_t^{\eta(i)},\ i\in\mathcal{L}_j\right\}_{t=0}^{\infty}} \sum_{\tau=0}^{\infty} \sum_{i\in\mathcal{L}_j} \delta^t \pi_{t+\tau}^j \tag{24}$$

subject to the law-of-motion in equation (22). In this latter problem, we allow the firm to commit to (say) period $t+1$ production in period t. However, the solution to this problem is time-inconsistent since, once period t passes, the firm no longer wishes to internalize the effect of period $t+1$ production on her period t profits and, in the absence of commitment, would change her period $t+1$ production plans. This commitment ability is eliminated in the problem characterized by equations (19) and (20).[22]

2.3 Linear-quadratic specification

Although solving for the Markov-perfect equilibrium of our dynamic game can be computationally severe,[23] we simplify its structure by specifying a linear-quadratic version of this model. In order to derive the linear-quadratic formulation, we make three functional form assumptions. First, we assume that the preference parameter θ is uniformly distributed (with total measure M) over $[0, \bar{\theta}]$, so that $F(\theta) = \theta/\bar{\theta}$. This assumption implies that the inverse demand functions in equation (9) are linear and given by

$$\begin{aligned} p_t^{\eta(i)} =& \bar{\theta}\left(\alpha_{\eta(i)}\left(1-\sum_{r=1}^{\eta(i)}\frac{1}{M}x_t^r\right) - \sum_{r=\eta(i)+1}^{K}\alpha_r\frac{1}{M}x_t^r\right) + \\ & \bar{\theta}\sum_{h=1}^{T_i-1}\delta^h\left(\alpha_{v^h(\eta(i))}\left(1-\sum_{r=1}^{v^h(\eta(i))}\frac{1}{M}x_{t+h}^r\right) - \sum_{r=v^h(\eta(i))+1}^{K}\alpha_r\frac{1}{M}x_{t+h}^r\right). \end{aligned} \tag{25}$$

Second, we assume the marginal costs of production are constant and independent across car models, so that $C_j(x_t^{\eta(i)}; \forall i \in \mathcal{L}_j) = \sum_{i\in\mathcal{L}_j} c_i$.[24]Finally, we assume that firms' production strategies $g_i(\cdot)$ are linear functions of the state and the value functions, $V_j(\cdot)$ are quadratic.

[22]Hence, we can also refer to the optimal production paths from the problem in equation (24) and the dynamic optimization problem in equation (19) as, respectively, the open and closed-loop problems.

[23]However, Rust (1997) and Pakes and McGuire (2001) have recently developed stochastic algorithms to alleviate the "curse of dimensionality" in the computation of dynamic models with large state spaces (including dynamic oligopoly models).

[24]This assumption was also maintained in the existing empirical literature on automobiles (cf. Bresnahan (1981), Berry, Levinsohn, and Pakes (1995)). The present framework can be easily extended to accommodate quadratic cost

By substituting these functional forms into the per-period profit function given by equation (17), we find that the firm's dynamic programming problem in equation (21) is a linear-quadratic problem in the state vector $\boldsymbol{A}\boldsymbol{y}_{t-1}$.

Given these assumption, we can rewrite each firms' dynamic programming problem (given by equations (21)–(23)) in matrix notation. To simplify the notation, we introduce K matrices, $\boldsymbol{R}_1, \ldots, \boldsymbol{R}_K$, which contain the linear coefficients from the inverse demand functions for cars $k = 1, \ldots, K$, respectively, in equation (25). [25] Subsequently, each firm's Bellman equation (21) takes the matrix form

$$\boldsymbol{y}_{t-1}'\boldsymbol{A}'\boldsymbol{S}_j\boldsymbol{A}\boldsymbol{y}_{t-1} = \max_{x_t^{\eta(i)}, \forall i \in \mathcal{L}_j} \left\{ \sum_{i \in \mathcal{L}_j} \left[\sum_{h=1}^{T_i} \delta^{h-1} \boldsymbol{y}_{t+h-1}' \boldsymbol{R}_{\omega(i,h)} \boldsymbol{y}_t \right] \right\} - \boldsymbol{y}_t'\boldsymbol{C}_j\boldsymbol{y}_t + \delta \boldsymbol{y}_t'\boldsymbol{A}'\boldsymbol{S}_j\boldsymbol{A}\boldsymbol{y}_t, \quad (26)$$

where, for $h = 1, \ldots, T_i - 1$,

$$\boldsymbol{y}_{t+h} = \boldsymbol{A}\boldsymbol{y}_{t+h-1} + \boldsymbol{B}\boldsymbol{d}_{t+h}, \quad (27)$$

and

$$\boldsymbol{d}_{t+h} = \boldsymbol{G}\boldsymbol{A}\boldsymbol{y}_{t+h-1}. \quad (28)$$

In these equations, (i) $\boldsymbol{S}_j$ is the $(K+1) \times (K+1)$ matrix of coefficients in firm j's value function, which is quadratic in $\boldsymbol{A}\boldsymbol{y}_t$; (ii) $\boldsymbol{C}_j$ is the $(K+1) \times (K+1)$ cost matrix for firm j, which contains c_i in the $(1, \eta(i))$-th entry for all $i \in \mathcal{L}_j$ and zeroes everywhere else; and (iii) $\boldsymbol{G}$ contains the coefficients of the linear equilibrium production rule. In the rest of this section, we solve for the Markov-Perfect equilibrium of this problem and derive $\boldsymbol{G}$, the matrix of production rule coefficients, as a function of the underlying model parameters.

First, we substitute recursively the linear equilibrium production rule (equation (28)) into the law of motion for the cars transacted (equation (27)), and write the law of motion as

$$\boldsymbol{y}_{t+h} = \left[(\boldsymbol{I} + \boldsymbol{B}\boldsymbol{G})\,\boldsymbol{A}\right]^h \boldsymbol{y}_t, \text{ for } h = 1, \ldots, T_i - 1. \quad (29)$$

Then, substituting equation (29) into equation (26), we rewrite firm j's dynamic programming

functions of the form $C_i(x_t^{\eta(i)}; \forall i \in \mathcal{L}_j) = \sum_{i \in \mathcal{L}_j} \left(c_{1i} x_t^{\eta(i)} + c_{2i} \left(x_t^{\eta(i)} \right)^2 \right)$.

[25] Specifically, for each car model $i \in \mathcal{L}$, we define matrices $\boldsymbol{R}_{\omega(i,h)}$, for $h = 1, \ldots, T_i$, which are $(K+1) \times (K+1)$ matrices with zeros everywhere except for the $\eta(i)$-th column (the column that corresponds to the quality ranking of a new model i). This column is set to

$$[\alpha_{\eta(i)}\bar{\theta}, \underbrace{-\alpha_{\eta(i)}\frac{\bar{\theta}}{M}, \ldots, -\alpha_{\eta(i)}\frac{\bar{\theta}}{M}}_{\text{entries } 2, \ldots, \eta(i)}, \underbrace{-\alpha_{\eta(i)}\frac{\bar{\theta}}{M}, -\alpha_{\eta(i)+1}\frac{\bar{\theta}}{M}, \ldots, -\alpha_K\frac{\bar{\theta}}{M}}_{\text{entries } \eta(i)+1, \ldots, K+1}]'.$$

problem as

$$y'_{t-1}A'S_jAy_{t-1} = \max_{x_t^{\eta(i)},\forall i\in\mathcal{L}_j} y'_t \left\{ \left[\sum_{i\in\mathcal{L}_j} \sum_{h=1}^{T_i} (A')^{h-1}[(I+BG)']^{h-1}\delta^{h-1}R_{\omega(i,h)} \right] - C_j + \delta\left[A'S_jA\right] \right\} y_t$$
$$\equiv \max_{x_t^{\eta(i)},\forall i\in\mathcal{L}_j} y'_tQ_jy_t = \frac{1}{2}y'_t\left(Q_j+Q'_j\right)y_t. \tag{30}$$

To solve for the equilibrium decision rule, we first let B_j denote the $(K+1)\times L_j$ matrix formed by extracting the columns of B corresponding to the $\mathcal{L}_j$ models produced by firm j. Therefore, the $L_j \times 1$-system of first order conditions for equation (30) becomes

$$B'_j\left(Q_j+Q'_j\right)Ay_{t-1} + B'_j\left(Q_j+Q'_j\right)Bd_t = 0. \tag{31}$$

Define the $(L_j\times(K+1))$ matrices $W_j \equiv B'_j\left(Q_j+Q'_j\right)$ for each firm j, and the $(K+1)\times(K+1)$ matrix $W \equiv [W_1,\ldots,W_N]'$. Then, stacking the systems of first-order conditions for all N firms as

$$WAy_{t-1} + WBd_t = 0, \tag{32}$$

we write the industry-wide system of equilibrium decision rules as

$$d_t = -(WB)^{-1}(WA)\,y_{t-1}, \tag{33}$$

which take the form of the equilibrium decision rule given by equation (28), with

$$G \equiv -(WB)^{-1}W. \tag{34}$$

In the present problem, we solve for the Markov-Perfect equilibrium production strategies using a value iteration procedure. We consider a long but finite-horizon version of the game and, starting from the terminal period, solve recursively for each firm's optimal production strategies via backwards induction. Under certain conditions, the sequence of production decision rules and value function coefficients converges to the unique linear Markov Perfect Equilibrium of the infinite-horizon game.[26] Consequently, for every set of parameter values, we use backward induction over the Bellman equation (30) to compute the equilibrium production strategies. Since the details of this procedure are standard, we leave them for the Appendix, Section D.2.[27]

[26] See Başar and Olsder (1982), Section 5.5, for more details of these conditions for linear-quadratic games. We note that existence in the present oligopoly problem is not guaranteed since it depends on the parameter values; as in an oligopoly problem, we require that the reaction functions intersect over the relevant output range. See also Judd (1996), pg. 11, for a similar discussion.

[27] In practice, the value iteration procedure converged very quickly, typically within 30 iterations (requiring about 5 seconds of CPU time).

In addition, a useful property of a linear-quadratic problem is the certainty equivalence property (cf. Sargent (1987), sect. 1.8), which implies that the derivations in this section generalize if we introduce additive shocks to demand as well as production costs, as long as consumers and producers have rational expectations regarding future realizations of prices.

3 Empirical Applications: the Automobile Market 1971–1990

While the production dynamics in durable goods oligopoly with homogeneous goods have been explored analytically in Esteban (2001), it is difficult to gain a more precise understanding of equilibrium producer behavior in a differentiated-products setting without particular values for the model parameters. We obtain values of these parameters by estimating a version of the linear-quadratic model using production and price data for the automobile industry, for the years 1971–1990.[28] For new cars, we use data on list prices and quantities collected from past issues of *Ward's Automotive Yearbook*.[29] We manually compiled secondary market prices from back issues of the *Kelley Blue Book* (western US edition).[30]

3.1 Assumptions for empirical implementation

Estimation of the durable-goods oligopoly model is complicated by the fact that the dimensionality of the state vector Ay_{t-1} grows very quickly in both the number and lifespan of each car model. We curtail this "curse of dimensionality" in several ways. First, we assume that all cars (new or used) have constant quality over time. Therefore, the quality of a car depends only on its model and age, not on the year it was produced.[31]

Second, we shorten the lifespan of all models to two years ($T_i = 2,\ \forall i \in \mathcal{L}$) and assume that one period in the theoretical model corresponds to one calendar year. This modeling assumption is justified by simulations for a durable goods monopolist, which show that production older than two or three years does not significantly affect current production decisions as long as the quality depreciation is not too small.[32] Nevertheless, to minimize any potential distortions occasioned by this assumption on the demand side, we amend our model to award owners of one-year old cars an exogenous (but positive) residual payment for their cars. In this way, we capture the residual value of cars beyond their second year of life (see Appendix B.1 for more details). In all the specifications considered below, the residual payment for each model is set equal to the observed price of a two-year old version of the model, and allowed to vary across years.[33]

Third, we focus our attention to seven models which we deem representative of the most popular automobile models during the twenty-year sample period considered (1971 to 1990): the Ford Pinto and Escort, the Chevrolet Impala and Cavalier, the Oldsmobile Cutlass, the Toyota Camry, and the

[28] The ready availability of detailed data on secondary market prices in the auto market is an important reason that we selected this market as an application of the model. However, we note that certain assumptions of our dynamic model — most notably the uni-dimensional differentiation between competing brands — are less appropriate for the auto market.

[29] This is the same dataset employed in Berry, Levinsohn, and Pakes (1999), and can be obtained online at `http://www.econ.lsa.umich.edu/~jamesl/verstuff/instructions.html`.

[30] We thank Bruce Hamilton for providing these old issues.

[31] As specification checks, we have re-estimated a version of the model allowing the quality ladder parameters (the α's) as well as the marginal cost parameters to be different in the 1980's versus the 1970's; since the results did not change qualitatively, we do not report them below.

[32] See Esteban (1999) for more details.

[33] We also estimated specifications in which the scrappage value is fixed at an average value across all years; the results were largely robust to this specification check.

Honda Accord. None of these models underwent substantial style changes during our sample period, which make them appropriate for our modeling framework given our assumption that the qualities of car models are fixed over time.[34] To minimize the distortions occasioned by only considering a small number of car models, we introduce two composite goods into consumers' choice sets to proxy for other automobile models available to consumers during the sample period. These two composites consist of (i) all other new cars; and (ii) all other one-year old used cars which do not correspond to one of the seven models listed above. Given these market definitions, the "outside good" for our empirical model is a composite product consisting of any used car two years old or older.[35]

Almost all of the seven car models either entered or exited the market during the sample period, and only the Oldsmobile Cutlass was available during the entire twenty-year period spanned by our data.[36] We include a model in consumers' choice sets in a given year only when that model was produced during that year. Therefore, the cars available to consumers during the sample period (1971–1990) are

New Pinto and one-year old Pinto (only 1971–1980),
New Escort and one-year old Escort (only 1981–1990),
New Impala and one-year old Impala (only 1971–1985),
New Cavalier and one-year old Cavalier (only 1981–1990),
New Cutlass and one-year old Cutlass (all years),
New Accord and one-year old Accord (only 1976–1990),
New Camry and one-year old Camry (only 1983–1990),
Composite 1: Any other new car (all years),[37]
Composite 2: Any other one-year old car (all years),
Outside good: a used car with age exceeding one year (all years).

Additional details on the construction of the variables in our dataset are given in Appendix B.2. Table 1 provides summary statistics of the data. In what follows, we will use the term "used" as shorthand for "one-year old".

[34] The upgrading of the Camry and Accord occurred after our sample period, in the early 1990s.

[35] In our empirical work, we also consider different definitions of market size.

Earlier (in Section 2.1), we set α_{K+1} and p_t^{K+1}, the quality and price of the outside good, to zero, across all t. When the outside good is defined as a used car with age exceeding one year, by normalizing p_t^{K+1} to zero for all t, we implicitly assume that the price of the cars in this category maintains a constant differential with the other cars in consumers' choice sets. This is not an unreasonable assumption, the more so due to the difficulty in obtaining data on the average prices of used cars by age.

[36] Since questions of entry and exit are beyond the scope of this paper, we assume that the entry and exit of models occurs exogenously, and is unforeseen by all agents.

[37] We assume that the stocks of cars in the two composite categories evolve exogenously according to a random walk process and is taken as given by all agents (both producers as well as consumers). We provide details on how we accommodate this within our linear-quadratic structure in Section A.3 of the Appendix.

We could have alternatively assumed that "Other one-year-old cars" in any period t equals the stock of "Other new cars" in the period $t-1$. However, one problem with this approach is that the total of cars transacted would not aggregate up to a market size equaling the cars in use figures from Polk (as reported in Cohen and Greenspan (1996)), which we use in our analysis.

3.2 Estimation procedure

Although the important demand and supply relations in this market are given by linear equations (equations (8) and (33)), least squares estimation of the reduced-form equations will not allow us to recover the structural parameters, since they are very nonlinear functions of the reduced-form regression coefficients.[38] Instead, we undertake direct structural estimation via a nested Generalized Method of Moments (GMM) procedure where a value iteration procedure to compute the equilibrium production rules is nested inside an outer loop which searches over parameter values matching the predicted population moments of the data-generating process (which are functions of the parameters) to their sample counterparts. In the rest of this section, we discuss the derivation of these moment conditions.

Up to this point, we have not introduced structural errors — factors observed by the agents in the model but unobserved by the econometrician — into the model.[39] Hence, the model does not generate as much randomness as we observe in the data. Specifically, the equilibrium ordering inequalities on prices and qualities of the cars (given in equation (10)) place restrictions on the values that the α parameters can take, given the observed prices. Since we assume these parameters to be constant over time (see next section), there is not enough variation in our model to explain the large variation in observed prices across time: essentially, without additional sources of randomness, our model is overidentified relative to the data.

Therefore, in order to motivate the empirical approach that we take, we introduce shocks to firms' marginal costs of production, so that the total (variable) cost associated with production level $x_t^{\eta(i)}$ is $x_t^{\eta(i)}\,(c_i + \epsilon_{it})$. If we assume that the vector of cost shocks $\epsilon_t \equiv [\epsilon_{1t}, \ldots, \epsilon_{Lt}]'$ is a zero-mean vector which is *i.i.d.* across all periods t, then we can appeal to a form of the certainty-equivalence property of linear-quadratic games to derive that the vector of optimal production rules in the presence of cost shocks is

$$\boldsymbol{d}_t = \boldsymbol{G}\boldsymbol{A}\boldsymbol{y}_{t-1} + \boldsymbol{w}_t \tag{35}$$

where $\boldsymbol{w}_t$ is a vector of linear functions of the cost shocks $\epsilon_{1t}, \ldots, \epsilon_{Lt}$ with zero mean.[40] Therefore, the decision rules with cost shocks (35) are equal to the decision rules without cost shocks (in equation (28)) plus an additive component which is stochastic from the econometrician's point of view, but with mean zero (and, furthermore, uncorrelated with $\boldsymbol{y}_{t-1}$) and independent over time.

In addition, in the presence of cost shocks, consumers will no longer have perfect foresight regarding the evolution of future prices on the equilibrium path. More precisely, the linear inverse demand

[38] Furthermore, reduced-form estimation is difficult due to the large number of reduced-form parameters. Note that the reduced-form for the supply-side alone (given by system of equations (33)) is a vector autoregression with $L \times (K+1)$ parameters (the elements of the $\boldsymbol{G}$ matrix). Estimating such a large number of parameters using our relatively short yearly time series on car production is infeasible.

[39] On the other hand, time-invariant model-specific effects (unobserved heterogeneity) are accommodated by estimating a separate α for each car model.

[40] A similar result obtains if we allow for demand shocks, so that the demand functions given in equations (6) above are subjected to additive shocks which are *i.i.d.* across time.

functions in period t becomes

$$p_t^{\eta(i)} = \left(\alpha_{\eta(i)} - \alpha_{\eta(i)+1}\right)\left(1 - \frac{1}{M}\sum_{r=1}^{\eta(i)} x_t^r\right) + \delta E\left[p_{t+1}^{v(\eta(i))}|\Omega_t\right] + p_t^{\eta(i)+1} - \delta E\left[p_{t+1}^{v(\eta(i)+1)}|\Omega_t\right], \quad (36)$$

where Ω_t denotes consumers' information sets as of period t. This is the stochastic analogue of equation (8) above. Given the linearity of this equation, and our stochastic assumptions regarding the cost shocks, it is easy to derive that

$$E\left[p_t^{\eta(i)} - \left(\alpha_{\eta(i)} - \alpha_{\eta(i)+1}\right)F^{-1}\left(1 - \frac{1}{M}\sum_{r=1}^{\eta(i)} x_t^r\right) + \delta p_{t+1}^{v(\eta(i))} + p_t^{\eta(i)+1} - \delta p_{t+1}^{v(\eta(i)+1)}\middle|\Omega_t\right] = 0 \quad (37)$$

Equations (35) and (37) are the main estimation equations for our model.[41]

The model parameters which we estimate are (i) $\alpha_1, \ldots, \alpha_K$, the qualities of the competing cars; (ii) $c_1, \ldots, c_L$, the constant marginal production costs for the new cars; and (iii) $\bar{\theta}$, the upper bound of the consumer heterogeneity distribution.[42] We estimate these parameters via GMM, using population moment restrictions implied by equations (35) and (37). Since they are largely standard, we omit the details of the GMM procedure here, but present them in Appendix D.1.

4 Empirical findings

Estimation results from three specifications of the model are presented in Table 2. The three models differ in their definition of the market size, and therefore the definition of the outside option. In Model I, the market is the total cars in use, so that the outside option is all used cars aged two year or older. For Model II, the market is the total of cars in use aged three years or younger, so that the outside option becomes all used cars aged between 2 and 3 years. Finally, in Model III the market is the total of cars in use aged two years or younger, so that the outside option is all two-year old used cars.[43] The markups corresponding to our estimated magnitudes of marginal cost are presented separately in Table 4. The markups are evaluated at the average (across-time) list price of a car model, in 1983$.

The main results appear robust across all three specifications. Furthermore, the figures in the penultimate row of Table 2 indicate that, for all three specifications, more than half of the inequalities required for demand with a cutoff structure to obtain (cf. the end of Section 2.1.2) are satisfied at the estimated parameter values, and for the realized prices. This suggests that we are not attributing an undue proportion of the price variation in the data to the cost shocks.

[41] Furthermore, in the presence of cost shocks, the inequalities in equations (10) or (11) must only hold for the *expected* rental prices $p_t^k - E_t\delta p_{t+1}^{v(k)}$, and not necessarily for the actual *realized* rental prices $p_t^k - \delta p_{t+1}^{v(k)}$. Thus we see that introducing these shocks into our model also loosens some of the equilibrium restrictions.

[42] As is usual in empirical dynamic models, the discount factor δ is not estimated, but rather fixed (at 0.95, in our case).

[43] See Appendix C for more details on market size.

Given the similarity in results across the three specifications, we will focus on the Model II results in what follows. Generally, the marginal cost estimates are precisely estimated, but the quality ladder parameters (the α's), while reasonably precise given the small (twenty years) sample span of our data, have larger standard errors.

First, we explore the quality ladder parameter estimates (the α's). For expositional ease, we group cars on the basis of their estimated α's into four quality tiers (where cars are grouped into a common tier if their estimated α's are close in magnitude). While the estimates of the α's change across the three specifications, tier membership (as given in the "Tier" column of Table 2) is constant. The top Tier A contains only the "Other new cars" composite and the new Impala. Tier B contains the new Pinto as well as both the new and used Cutlass. Tier C, the largest tier, contains the new Escort, used Impala, new Cavalier, and both the new and used Camry and Accord. The lowest tier, Tier D, consists of used Escorts, Cavaliers, Pintos, and the "Other one-year old cars" composite. Furthermore, the relative sizes of the tiers reflect a "clustering" of products at the lower-end of the quality spectrum: this is a natural feature in vertically-differentiated durable-goods markets with depreciation, since high-quality new products evolve into lower-quality used products as they age.

Our results also show that the Cutlass, Accord, and Camry depreciate very slowly (in the sense that the new and used variants of each model are in the same tier), which is consistent with general market perceptions of these cars.[44] In addition, Table 1 shows that, generally, models which we estimate to depreciate faster had lower production: for example, production of the slow-depreciating Camry and Accord averaged only 170,985 and 233,187 units (respectively) per year, while the Escort and Cavalier — both of which depreciate more quickly — averaged 352,725 and 305,531 units, respectively. This is consistent with our dynamic oligopoly model, where producers of slow-depreciating cars face more intense competition from their past production, and therefore have a greater incentive to lower equilibrium production.

In order to study the estimated quality of each car model, in Table 3 we report the total discounted quality (hereafter TDQ) for each car model in our data set. The TDQ for a given car model is computed as $\alpha_{new} + \delta * \alpha_{used}$, where α_{new} and α_{used} are, respectively, the estimated qualities for a new and one-year old version of the car model. The TDQ measure adjusts naturally for the estimated quality depreciation of each car model, so that cars which depreciate mode quickly (in terms of quality) will, *ceteris paribus*, have a lower TDQ. The rankings among car models, in terms of TDQ, are consistent with general market perceptions of these models. In the 1971 choice set, for example, the TDQ's of the higher-end (and larger) Cutlass and the Impala (2.014 and 1.918, respectively) are substantially higher than the TDQ for the lower-end and smaller-sized Pinto (1.435). Similarly, using the 1990 choice set, we find that the rankings among the car models, using the TDQ, is (Cutlass, Accord, Camry, Cavalier, Escort) which, indeed, corresponds to general market perceptions.

To gauge the relation between our marginal cost and quality estimates, we regressed our estimates

[44] Both the Camry and the Accord were upgraded substantially in the early 1990s, and we conjecture that more recent data should show that these cars are no longer "Tier C" cars.

of marginal cost on our estimates of quality, which yields (for the Model II results):[45]

$$COST = \underset{(1.191)}{2.086} + \underset{(2.668)}{5.185} * \alpha_{new} - \underset{(-2.140)}{3.614} * DEPR \quad (N = 7,\ R^2 = 0.701) \tag{38}$$

where α_{new} denotes the quality of a new model, and the depreciation rate $DEPR$ is calculated as $(\alpha_{new} - \alpha_{used})/\alpha_{new}$. Consistently with economic intuition, the regression (38) indicates a precisely-measured positive relation between production costs and new car quality, and negative relation between depreciation rate and costs. As this relation was not imposed in the estimation procedure, we take it as another confirmation of the reasonableness of our empirical results.

The marginal cost estimates (cf. Table 4) indicate that markups are highest for the Escort and the Cavalier, at 50.5% and 57.7%, respectively. It is not surprising that these models are also the ones which had the highest production levels out of the seven models in our dataset since, *ceteris paribus*, cars with (relatively) lower production costs will be produced more. Similarly, we estimate the lowest markups for the Impala and Cutlass (25.1% and 27.3%, respectively), both of which had more modest production levels on average, during the sample period. The high estimated markup (44.2%) and low observed output of the Camry contradicts this trend. In our dynamic model, however, this apparent contradiction is, in fact, consistent with the Camry's low output. As we argued in the previous paragraph, the Camry's slow depreciation implies that new Camrys substitute well with used Camrys. This provides strong incentives for Toyota to curtail production of the Camry.

Dynamic equilibrium production rules Table 5 contains the equilibrium production rules computed from equation (33) using the results from Model II. Three sets of decision rules are presented, corresponding to the market definitions in 1971, 1981, and 1990.

The generally negative coefficients on the used car stocks indicate that equilibrium production is *decreasing* in stocks in the secondary market: this is due to the strategic substitutes aspect of the oligopoly quantity-setting game we consider. In addition, the largest (in magnitude) coefficients are attached to cars which are the closest substitutes. For example, for the 1981 choice set, we see that Impala production is more responsive to the production of "Other new cars" (coefficient -0.2574), than to past Impala production (coefficient -0.0690). This reflects our result that the "Other new cars" composite is a closer substitute for the new Impala (both are Tier A cars) than a used Impala (which is in Tier C). On the other hand, production of the new Cutlass is quite sensitive to the stock of used Cutlasses (coefficient -0.1941), since we estimate the Cutlass to depreciate very slowly (both the new and used Cutlass are in Tier B).

4.1 Counterfactual experiments

In these counterfactual experiments we aim to understand how durability and secondary markets can affect producers' dynamic behavior. First, we analyze the value of commitment in durable goods

[45]T-statistic in parentheses. Similar results were obtained for the Models I and III estimates.

markets and, second, we explore the profitability of a planned obsolescence strategy in a durable goods oligopoly.

Table 6 contains results from counterfactual simulations employing the estimates from Model II (the 1981 choice set), which consists of the Ford Escort, Chevy Cavalier and Impala, and the Honda Accord.[46] Panel I of this table contains the simulated values for *(i)* steady-state equilibrium production (in millions of units); and *(ii)* the corresponding per-period profits (in billions of dollars). The other panels in this table contain results from the two sets of counterfactual experiments. For ease of comparison, we report the results from the counterfactual experiments in percentage changes relative to the baseline results.

Comparing the simulated steady-state production levels in Panel I to the actual values in Table 1, we see that the simulated values are generally larger but, except for the Cutlass, of the same order of magnitude. This fit is reasonable, given the large number of alternatives in the car market, and the small (in absolute terms) market shares of the seven car models we consider.

Profitability of full-commitment Panel II of Table 6 contains results from industry simulations under the counterfactual assumption that firms are able to commit fully to all future production levels.[47] In a monopoly setting, the ability to commit always increases profits. The simulation results here suggest that firms' profits increase with the ability to commit in the present oligopolistic setting as well: profits from the Escort, Impala, Cutlass, and Accord increase by 164%, 87%, 3% and 202%, respectively, relative to the baseline results, which were computed assuming no commitment. These results support Coase's conjecture that the inability to commit erodes a firm's profits.

In the monopoly setting, these higher profits can only achieved by decreases in production, as shown in the Coase Conjecture literature. Indeed, in our oligopoly results, aggregate production decreases by 8.5%, relative to the baseline results.[48] However, changes in production vary across car models. On the one hand, the commitment effect leads firms to cut back production, but on the other hand, strategic considerations may lead firms to increase production in response to rivals' cutbacks.

In our vertically-differentiated setting, the net effects are asymmetric between higher-end and lower-end cars because higher-end cars are less substitutable with used cars than lower-end cars. This implies that, without commitment, the secondary market by itself is enough to encourage greater cutbacks in production for lower-end rather than higher-end producers. Therefore, by allowing firms to commit, we expect the commitment effect to dominate for higher-end firms, while strategic considerations may be more important for lower-end firms. This asymmetry in production effects is reflected in our results: while the production of the higher-end Cutlass and Impala decreases (by

[46] We also ran the experiments for the 1971 and 1990 choice sets, but they are qualitatively very similar to the 1981 results.

[47] We report the steady-state values of the full-commitment equilibrium path. See Appendix E for details on the methodology employed in these simulations. It is well-known that these full-commitment production levels can be implemented in a leasing equilibrium in which firms are forced to supply all their used vehicles to the secondary market. Hendel and Lizzeri (1999b) point out, however, that in these situations firms can generally do better by scrapping used vehicles rather than selling them in the secondary market.

[48] This number is calculated using results reported in Table 6.

2.6% and 30.4%, respectively), the production of the lower-end Escort and Accord increases, by 25.8% and 19.1% respectively.

Reductions in durability: profitability of planned obsolescence strategy In a second set of counterfactual experiments, we explore the effects of durability and secondary markets for oligopolistic producers by simulating the effects of unilateral reductions in the durability (resembling a planned obsolescence strategy) for each car model. In all these experiments, we assume that marginal costs are not affected by the reduction in durability to isolate dynamic effects.

Panel III of Table 6 shows that steady-state profits for three out of the four models increase substantially relative to their baseline levels when they become less durable (the percentage increases are 1064%, 162%, and 569%, respectively, for the Escort, Impala, and Accord). Profits for the Cutlass, on the other hand, only increased 0.6% as a result of a reduction in durability. This can be explained by the Cutlass's slow quality depreciation (both the new and used Cutlass are in Tier B), which creates a large investment motive for buying the Cutlass. However, this investment motive disappears once we reduce its durability and, indeed, these results indicate that this is enough to decrease the steady-state profits, despite the fact that the production of the less-durable Cutlass has increased by 34%.

As with the full commitment counterfactual experiments, there are significant differences in these results between the higher-end and the lower-end cars. For the Escort and the Accord, decreased durability not only increases the steady state production (and profits) of that product, but also decreases the production (and profits) of its rivals (by more modest percentages): for example, shortening the lifespan of an Escort increases its steady-state profits by 635.1%, but reduces the profits of all the other cars. The opposite result obtains for the higher-end Impala and Cutlass: for these models, decreased durability tends to increase production and profits across all car models. For example, reducing the durability of an Impala increases not only its steady-state profits by 162%, but also the profits of the Escort and the Accord.

The reason for these differences is apparent: a used Cutlass or Impala is a close substitute for a new Escort or Accord, so that decreasing the durability of the Cutlass and Impala would have a strong positive effect on Escort and Accord production, in the quantity-setting game we consider. On the other hand, a used Escort or Accord is not very closely substitutable with a new Impala or Cutlass. For the the Impala and the Cutlass, therefore, the production-curtailing effects arising from the higher production of new Escorts and Accords dominate the production-increasing effect arising from the elimination of used Escorts and Accords.

This immediately suggests that higher-end car producers may benefit more from the durability of their products than lower-end producers. Indeed, there may be an incentive for producers of higher-end models to make their cars more durable in order to compete more effectively with lower-end cars. Producers of lower-end cars, however, have the opposite incentive because they compete vigorously with their past production. This asymmetry in the profitability of a planned obsolescence strategy between producers at different ends of the quality spectrum appears to be a unique feature of a vertically-differentiated durable goods oligopoly where products depreciate over time.[49] Perhaps it also explains the absence of durable cars at the lower-end, and nondurable cars at the higher-end, of the car market.

5 Conclusions

In this paper we develop a model of dynamic oligopoly to understand the intertemporal links which arise from durability of the product and its trade in secondary markets. We use a tractable linear-quadratic specification of the model to obtain estimates of the structural parameters and calculate each producer's equilibrium decision rule. To our knowledge, we are the first to estimate such a dynamic equilibrium model for the car industry.

While the linear-quadratic structure has allowed us to uncover new insights into the effects of durability and secondary markets in the automobile industry, we plan to explore alternative models which may allow us to incorporate additional problems which have been shown in the existing literature to be important in the automobile industry, such as transaction costs, asymmetric information, and inventories. However, incorporating these features in the context of a fully dynamic oligopoly model with secondary markets leads to substantial difficulties.

[49] However, this feature may not arise in durable goods markets when products can appreciate over time, such as wine or art markets.

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A Dynamic optimality of the consumers' problem

Here we prove that our assumptions of quasilinear per-period utility function and zero transactions costs imply that consumers' optimal car choices take the form described in Section 2.1.1. We consider a consumer of type θ who enters period t owning a used car of quality ranking k (where $k = K+1$ denotes ownership of no car).

$W_t^\theta(k)$, consumer θ's value function at the beginning of period t, must satisfy the Bellman equation

$$\begin{aligned} W_t^\theta(k) &= \max\left\{\alpha_1\theta - p_t^1 + p_t^k + \delta W_{t+1}^\theta(v(1)), \dots, \alpha_K\theta - p_t^K + p_t^k + \delta W_{t+1}^\theta(v(K)), 0 + p_t^k + W_{t+1}^\theta(K+1)\right\} \\ &= p_t^k + \max\left\{\alpha_1\theta - p_t^1 + \delta W_{t+1}^\theta(v(1)), \dots, \alpha_K\theta - p_t^K + \delta W_{t+1}^\theta(v(K)), 0 + W_{t+1}^\theta(K+1)\right\} \\ &= p_t^k + W_t^\theta(K+1). \end{aligned} \tag{39}$$

Since this holds for all t, it implies that

$$W_{t+1}^\theta(k) = p_{t+1}^k + W_{t+1}^\theta(K+1), \tag{40}$$

Next, we substitute equation (40) into the second equation in (39) for each car k, and eliminate the constant terms common to all the utility levels (these are $W_{t+1}^\theta(K+1)$ and p_t^k). Then, the consumer determines her optimal consumption decision by solving

$$\begin{aligned} &\max\{\alpha_1\theta - p_t^1 + \delta p_{t+1}^{v(1)}, \dots, \alpha_K\theta - p_t^K + \delta p_{t+1}^{v(K)}, 0\} \\ =&\max\{UG_t^1(\theta), \dots, UG_t^K(\theta), 0\}, \end{aligned}$$

as posited in Section 2.1.1.

B Model extensions

B.1 Accommodating exogenous scrappage

In the current problem, the dimensionality of the state space grows quickly as we increase the durability of each car. In order to minimize this curse of dimensionality in the empirical implementation, we shorten the durability of cars. As described in Section 3.1, we assume that each car lasts only two years. To reduce the distortions arising from this assumption, we assume that owners of two-year old cars, while not being able to trade them in secondary markets, are able to obtain some nonzero scrappage value (or residual payment) for their cars. In this section we extend the model described in the main text to accommodate this scrappage value.

More precisely, we assume that each car model $i \in \mathcal{L}$ is scrapped after s_i (where $s_i \leq T_i$) periods of life for a scrappage value $\mathcal{S}_{i,t}$.[50] We assume that consumers derive no utility from the consumption of a car older than s_i years. Hence, all consumers will scrap their cars at this age, since by doing so they obtain additional income in the form of the scrappage value.[51]

[50] We do not endogenize the sector for car scrappage; that is, we take the scrappage date s_i as given. This approach differs from, for example, Rust (1985b), in which the scrappage market is endogenized by allowing consumers to optimally choose the date at which to scrap their cars.

[51] If, instead, we had assumed that cars could be either scrapped or consumed, the scrappage value would then effectively constitute a price floor in the secondary markets. If this price floor binds, the linear-quadratic structure of the dynamic programming problem would not obtain.

For a given model $i \in \mathcal{L}$, in period t, we accommodate scrappage by reducing the lifespan of the car to $T_i = s_i$, and set the period t scrappage value $\mathcal{S}_{i,t}$ of this model equal to the resale price of car $(i, s_i + 1)$ in period t: $\mathcal{S}_{i,t} \equiv p_t^{v^{s_i+1}(\eta(i))}$. With these changes, the inverse demand function for a new car i is

$$p_t^{\eta(i)} = (\alpha_{\eta(i)} - \alpha_{\eta(i)+1})\bar{\theta}\left(1 - \frac{1}{M}\sum_{r=1}^{k} x_t^r\right) + \delta p_{t+1}^{v(\eta(i))} + p_t^{\eta(i)+1} - \delta p_{t+1}^{v(\eta(i)+1)}. \tag{41}$$

After some recursive substitution, this becomes

$$\begin{aligned} p_t^{\eta(i)} =& \bar{\theta}\left(\alpha_{\eta(i)}\left(1 - \sum_{r=1}^{\eta(i)} \frac{1}{M} x_t^r\right) - \sum_{r=\eta(i)+1}^{K} \alpha_r \frac{1}{M} x_t^r\right) + \\ & \bar{\theta}\sum_{h=1}^{s_i-1} \delta^h \left(\alpha_{v^h(\eta(i))}\left(1 - \sum_{r=1}^{v^h(\eta(i))} \frac{1}{M} x_{t+h}^r\right) - \sum_{r=v^h(\eta(i))+1}^{K} \alpha_r \frac{1}{M} x_{t+h}^r\right) + \delta^{s_i}\mathcal{S}_{i,t+s_i}. \end{aligned} \tag{42}$$

The linear-quadratic model then obtains by simply adding $\delta^{s_i}\mathcal{S}_{i,t+s_i}$ to the $(1, \eta(i))$-th entry of the matrix $\boldsymbol{R}_i$. All the other derivations follow.

B.2 Modeling cars for which production evolves exogenously

The linear-quadratic structure of this model is easily extended to accommodate models for which production evolves exogenously (i.e., is not set endogenously by an agent within the model). For expositional convenience, we will refer to these models as "imports" in this section, and refer to those models produced by agents within the model as "domestic" models.

Let $\mathcal{L}_m$ denote the set of all import models and $L_m \equiv |\mathcal{L}_m|$ their total number. For each model $i \in \mathcal{L}_m$, let $T_i < \infty$ denote the number of periods it lasts. Then, the set of all models transacted is $\bar{\mathcal{L}} \equiv \mathcal{L} \cup \mathcal{L}_m$, where $\mathcal{L}$ was previously defined to be the car models produced (now domestically produced), and $\bar{L} \equiv |\bar{\mathcal{L}}|$ is their total number. Hence, the total number of car models equals $\bar{K} = \sum_{i \in \bar{\mathcal{L}}} T_i$.

Recall that in the derivation of the model we labeled car models $i \in \mathcal{L}$ as $i = 1, \ldots, L$. Accordingly, we label domestic models by $i = 1, \ldots, L$, and import models by $i = L+1, \ldots, L + L_m$. First, we expand the quality ladder to incorporate the extra import models.

Second, we redefine the law of motion to incorporate the placement of import models. That is, we define a matrix $\boldsymbol{D}$ that places import models into the quality ladder. We let the dimensions of this matrix be $(\bar{K}+1) \times L_m$ and define each entry as follows: for all $i = L+1, \ldots, L + L_m$ and $k = 1, \ldots, \bar{K}$

$$\boldsymbol{D}(k+1, i) = 1, \quad \text{if } \eta(i) = k,$$

and equal to zero, otherwise. Then, we write the law-of-motion of all cars in use as

$$\boldsymbol{y}_t = \boldsymbol{A}\boldsymbol{y}_{t-1} + \boldsymbol{B}\boldsymbol{d}_t + \boldsymbol{D}\boldsymbol{x}_{mt},$$

where $\boldsymbol{x}_{mt}$ denotes the vector of imports. We now follow the discussion in the main text to derive the demand functions, and equilibrium production rules.

In our empirical implementation, the "Other new car" and "Other one-year old car" categories are modeled as imports, whose stocks evolve exogenously according to a random walk process. Furthermore, to simplify the empirical implementation, we attribute a lifespan of only one year for these cars, but assume that consumers receive a positive scrappage value (in the manner described in Appendix B.1 above) for these cars after one year of use. This should minimize the distortions arising from this assumption.

C Data appendix

Here we list additional assumptions made in constructing the dataset used in estimating the model.

The market size M differs across the three different specifications we estimated, the results of which are reported in Table 2. The three models differ in their definition of the market size, and therefore the definition of the outside option. In Model I, the market is the total of cars in use, and the outside option is all used cars aged two years or older. For Model II, the market is the total of cars in use aged three years or younger, so that the outside option becomes all used cars aged between two and three years. Finally, in Model III the market is the total of cars in use aged two years or younger, and the outside option is all two-year old used cars. The evolution of these three definitions of M during the sample period are as follows[52]

Year	Market size M_t, in millions		
	Model I	Model II	Model III
1971	60.4	32.3	24.4
1975	95.2	35.9	25.8
1980	104.6	36.7	26.8
1985	114.7	32.1	24.8
1990	123.3	36.1	25.9

Note that while the total number of cars in use (cf. column 1) rose dramatically across the twenty year sample period, the numbers of cars in use younger than 3 years (column 2) and younger than 2 years (column 3) remained largely constant, implying that the median age of a car in use rose significantly over the sample period.

Prices were deflated using a 1983 dollar as the base. Across all years, prices for the "Other new cars" category were taken from the "average expenditure per new car" series collected by the Bureau of Economic Analysis (BEA) at the US Department of Commerce. Since we were unable to obtain prices for used cars by vintage, the price of the "Other one-year old cars" category was set equal to 80% of the price of the "Other new cars".[53]

In all three model specifications, the scrappage values for the Pinto, Escort, Impala, Cavalier, Cutlass, Accord, and Camry in each year are set equal to the price of a two-year old model in that year (for example, the scrappage value for a Camry in 1987 is set to the secondary market price of a 1985 model-year Camry, in 1987). The scrappage value of the composite "Other new cars" in each year is set equal to the price of the "Other one-year old cars" in that same year. The scrappage value of the "Other one-year old cars" category in each year is set to 80% of the "Other one-year old cars" price in that same year.

[52]The source of this data is Polk, who compiled the data from car registration records. We thank Darrel Cohen for providing this data; see Cohen and Greenspan (1996) for more details on these data.

[53]We also estimated using a rate of 75%, and the results did not change appreciably.

D Estimation procedure: details

D.1 GMM Estimation

Let ψ denote the structural parameters of the model, which are (i) $\alpha_1, \ldots, \alpha_K$, the qualities of the competing cars; (ii) $c_1, \ldots, c_L$, the constant marginal production costs for the new cars; and (iii) $\bar{\theta}$, the upper bound of the consumer heterogeneity distribution. Let $\boldsymbol{X}$ denote the full set of observed quantities $\left[x_t^1, \ldots, x_t^K\right]'$, $t = 1, \ldots, T$ in the dataset. Let $\boldsymbol{\alpha} \equiv [\alpha_1, \ldots, \alpha_K]'$ denote the quality ladder, the parameters of which we want to estimate.

Supply side moment conditions For the supply side, the basic estimating equations are the equilibrium production rules linking current production of new cars to stock of used cars in the market (equations (35)):

$$\boldsymbol{d}_t = \boldsymbol{G}\boldsymbol{A}\boldsymbol{y}_{t-1} + \boldsymbol{w}_t,$$

where given our assumptions, the error vectors $\boldsymbol{w}_t$ are independent over time, and $E\left(\boldsymbol{w}_t \boldsymbol{y}_{t-1}\right) = 0$. Therefore, ordinary least squares is apprropriate for the supply rules (i.e., $\boldsymbol{y}_{t-1}$ are appropriate instruments). Hence, the sample analogue of these restrictions takes the form

$$\gamma_T^s(\psi) \equiv \frac{1}{T} \sum_t \left[\boldsymbol{d}_t - (\boldsymbol{G}\boldsymbol{A})\boldsymbol{y}_{t-1}\right] * \boldsymbol{y}_{t-1}. \tag{43}$$

The $\boldsymbol{G}$ matrix is, generally, a function of the model parameters ψ. However, the mapping between ψ cannot be expressed analytically, since it depends on the coefficients of the equilibrium value function (cf. equation (33) in the text). Therefore, we use a nested procedure in order to construct the moment conditions for the supply side. First, for every parameter vector ψ, we solve the linear quadratic dynamic programming problem given by equation (26) in order to obtain values for $\boldsymbol{G}(\psi)$, the matrix of production rule coefficients corresponding to the parameter vector ψ.

Demand side moment conditions The population moment restrictions for the demand which we use to estimate the model parameters is given in equation (37). Let z_t denotes a vector of instruments, which are elements of Ω_t, the information set of consumers for period t. In our specifications, z_t consists of the constant 1, current and lagged market shares, and current and lagged prices as instruments.

Therefore, the sample analogue of the demand-side moment restrictions for production of car $\eta(i)$ take the form

$$\gamma_{T,i}^x(\psi) \equiv \frac{1}{T} \sum_{t=1}^{T} \left[p_t^{\eta(i)} - \left(\alpha_{\eta(i)} - \alpha_{\eta(i)+1}\right) \left(1 - \frac{1}{M} \sum_{r=1}^{\eta(i)} x_t^r\right) + \delta p_{t+1}^{v(\eta(i))} + p_t^{\eta(i)+1} - \delta p_{t+1}^{v(\eta(i)+1)} \right] * z_t \tag{44}$$

and $\gamma_T^x(\psi) \equiv \left[\gamma_{T,1}^x(\psi), \ldots, \gamma_{T,L}^x(\psi)\right]'$ denotes the vector of sample demand-side moment conditions.

We obtain estimates of the structural parameters ψ via GMM, by minimizing a quadratic form in the sample moment conditions given in equations (44) and (43).

Let $\boldsymbol{\mu}_T(\psi) \equiv \begin{bmatrix} \gamma_T^s(\psi) \\ \gamma_T^d(\psi) \end{bmatrix}$. Our GMM estimator minimizes a quadratic form in $\boldsymbol{\mu}_T(\psi)$ given by

$$\boldsymbol{\mu}_T(\psi)' \boldsymbol{\Gamma}_T^{-1} \boldsymbol{\mu}_T(\psi)$$

where Γ_T is a (possibly deterministic) convergent sequence of weighting matrices.

Let ψ_T^{GMM} denote the vector of GMM estimates associated with a dataset with T periods of data. Under the usual assumptions, as $T \to \infty$ the sequence $\psi_T^{GMM} \xrightarrow{p} \psi_0$, and

$$\sqrt{T}\left(\psi_T^{GMM} - \psi_0\right) \xrightarrow{d} N\left(0, \left(J_0\Gamma_0 J_0'\right)^{-1} J_0\Gamma_0 H_0 \Gamma_0 J_0' \left(J_0\Gamma_0 J_0'\right)^{-1}\right), \tag{45}$$

where Γ_0 is the (probability) limit of the Γ_T sequence,

$$\begin{aligned} J_0 &= E_0 \frac{\partial \mu(\psi)'}{\partial \psi}, \\ H_0 &= \mathrm{Var}_0\left(\mu(\psi)\right), \end{aligned}$$

and E_0 and Var_0 denote expectation and variance with respect to the true data-generating process (i.e., under ψ_0). For the results reported in this paper, we employ a diagonal weighting matrix, in which each moment condition is weighted by the inverse of its (marginal) sample variance.

D.2 Deriving the equilibrium production rules

In this section we describe the value iteration procedure used to compute the Markov perfect equilibrium production rules. For all firms $j \in \mathcal{N}$, we begin with initial guesses for S_j^0, $j \in \mathcal{N}$ for their respective matrices of value function coefficients. Using these matrices, we calculate recursively, for $\tau = 1, 2, 3, \ldots$,

$$\begin{aligned} Q_j^\tau &\equiv A' S_j^\tau A, \ j \in \mathcal{N}, \\ W_j^\tau &\equiv B_j'\left(Q_j^\tau + Q_j^{\tau\prime}\right), \\ W^\tau &\equiv \left[W_1^\tau, \ldots, W_N^\tau\right]', \\ G^{\tau+1} &\equiv \left(W^\tau B\right)^{-1} W^\tau. \end{aligned} \tag{46}$$

In each iteration, we update the coefficient matrix for the value functions via

$$S_j^{\tau+1} = \left\{ \left[\sum_{i \in \mathcal{L}_j} \sum_{h=1}^{T_i} (A')^{h-1} [(I + BG^{\tau+1})']^{h-1} \delta^{h-1} R_{\omega(i,h)} \right] - C_j + \delta\left[A' S_j^\tau A\right] \right\}, \quad \text{for each } j \in \mathcal{N}.$$

We iterate this procedure until the sequence of matrices S_j^τ and G^τ converges. The converged values of these matrices are the coefficients of the equilibrium value functions and production rules, respectively.[54]

E Computing steady-state production levels under full commitment

In this section, we describe the procedure for simulating the steady-state full commitment production figures displayed in Table 6. Consider firm j, who produces all models in the set $\mathcal{L}_j$. Firm j's objective is to

$$\max_{\left\{x_t^{\eta(i)}\right\}_{t=1}^{\infty},\ i \in \mathcal{L}_j} \sum_{t=1}^{\infty} \pi_t^i. \tag{47}$$

[54] In practice, the value iteration process converged very quickly, often within 20 iterations.

Since each model lasts for only two periods,

$$\pi_t^i = \boldsymbol{y}_t' \boldsymbol{R}_{\omega(i,1)} \boldsymbol{y}_t + \delta \boldsymbol{y}_{t+1}' \boldsymbol{R}_{\omega(i,2)} \boldsymbol{y}_t. \tag{48}$$

Consider firm j's optimal choice of $x_t^{\eta(i')}$, $i' \in \mathcal{L}_j$, for some future period t. Since each model lives for two periods only, $x_t^{\eta(i')}$ enters as an argument in π_{t-1}^i, π_t^i, and π_{t+1}^i, for all $i \in \mathcal{L}_j$.

So for each $i' \in \mathcal{L}_j$, production $x_t^{\eta(i')}$ satisfies the first-order condition

$$\delta^{-1} \sum_{i \in \mathcal{L}_j} \frac{\partial \pi_{t-1}^i}{\partial x_t^{\eta(i')}} + \sum_{i \in \mathcal{L}_j} \frac{\partial \pi_t^i}{\partial x_t^{\eta(i')}} + \delta \sum_{i \in \mathcal{L}_j} \frac{\partial \pi_{t+1}^i}{\partial x_t^{\eta(i')}} = 0, \tag{49}$$

where

$$\begin{aligned}
\frac{\partial \pi_{t-1}^i}{\partial x_t^{\eta(i')}} =& \delta \boldsymbol{B}_{i'}' \boldsymbol{R}_{\omega(i,2)} \boldsymbol{y}_{t-1}, \\
\frac{\partial \pi_t^i}{\partial x_t^{\eta(i)'}} =& \boldsymbol{B}_{i'}' \left(\boldsymbol{R}_{\omega(i,1)} + \boldsymbol{R}_{\omega(i,1)}' \right) \boldsymbol{y}_t + \delta \left(\boldsymbol{B}_{i'}' \boldsymbol{R}_{\omega(i,2)}' \boldsymbol{y}_{t+1} + \boldsymbol{B}_{i'}' \boldsymbol{A}' \boldsymbol{R}_{\omega(i,2)} \boldsymbol{y}_t \right), \\
\frac{\partial \pi_{t+1}^i}{\partial x_t^{\eta(i')}} =& \boldsymbol{B}_{i'}' \boldsymbol{A}' \left(\boldsymbol{R}_{\omega(i,1)} + \boldsymbol{R}_{\omega(i,1)}' \right) \boldsymbol{y}_{t+1} + \delta \boldsymbol{B}_{i'}' \boldsymbol{A}' \boldsymbol{R}_{\omega(i,2)} \boldsymbol{y}_{t+2},
\end{aligned} \tag{50}$$

and $B_{i'}$ is the column in matrix B corresponding to car model i'.

In steady-state, $\boldsymbol{y}_{t-1} = \boldsymbol{y}_t = \boldsymbol{y}_{t+1} = \boldsymbol{y}_{t+2} \equiv \boldsymbol{y}^*$. We substitute $\boldsymbol{y}^*$ into the expressions in equation (50) and solve the first-order condition (49) for the steady-state car stock vector $\boldsymbol{y}^*$. These steady-state production values are used to compute the percentage changes reported in the Section A of Table 6.

F Tables and Figures

Table 1: Data: summary statistics

Variable	T	Mean	Std Dev	Minimum	Maximum
Quantities					
Pinto (Ford)	10	282,764.50	114,052.90	142,467.00	480,472.00
Escort (Ford)	10	352,725.80	46,993.48	284,907.00	420,690.00
Impala (GM)	15	263,878.73	218,587.33	40,394.00	577,313.00
Cavalier (GM)	9	305,530.78	86,485.68	121,392.00	431,031.00
Cutlass (GM)	20	263,194.85	136,651.90	92,779.00	527,939.00
Accord (Honda)	15	233,186.80	116,126.72	18,643.00	417,179.00
Camry (Toyota)	8	170,985.38	79,750.45	52,666.00	284,595.00
Other new	20	5,229,327.85	924,296.26	3,438,773.00	6,684,767.00
Other one-year old	20	8,475,130.55	1,041,835.47	6,468,773.00	9,965,767.00
Prices (1983 dollars):					
New Pinto (Ford)	10	6,039.57	411.70	5,500.00	6,812.67
One-year old Pinto	10	5,688.91	309.98	5,263.16	6,253.44
New Escort (Ford)	10	6,599.60	566.32	5,477.38	7,126.61
One-year old Escort	8	5,638.76	157.96	5,422.86	5,848.54
New Impala (GM)	15	9,283.38	441.48	8,502.25	9,966.24
One-year old Impala	16	8,117.66	871.99	6,981.98	9,447.85
New Cavalier (GM)	9	8,368.76	547.03	7,880.65	9,589.66
One-year old Cavalier	8	7,202.44	227.80	7,007.43	7,642.49
New Cutlass (GM)	20	9,739.81	1327.74	7,855.86	11,897.48
One-year old Cutlass	20	8,730.03	937.16	6,747.57	9,984.70
New Accord (Honda)	14	9,790.65	999.33	7,927.51	11,276.42
One-year old Accord	13	9,309.72	645.51	8,140.81	10,025.10
Camry (Toyota)	8	9,797.89	1583.85	8,080.83	11,942.52
One-year old Camry	6	9,369.62	531.99	8,691.05	10,161.29
Other new	20	10,371.35	1201.10	9,044.62	12,127.64
Other one-year old	20	8,297.08	960.88	7,235.70	9,702.11

Table 2: Estimation results

Parameter	Model I Estimate	Model I Std. Error[a]	Model I Ladder Ranking	Model II Estimate	Model II Std. Error	Model II Ladder Ranking	Model III Estimate	Model III Std. Error	Model III Ladder Ranking	Tier
Quality ladder α's[b]										
New Pinto	1.0178	1.8623	4	1.0258	1.2922	4	1.0060	0.2990	4	B
One-year old Pinto	0.4655	0.8157	13	0.4362	1.3598	15(tie)	0.5239	1.0269	13	D
New Escort	0.7308	2.3791	9	0.7303	1.1585	9(tie)	0.7445	0.4718	9	C
One-year old Escort	0.4441	1.8979	14(tie)	0.4433	1.0062	13	0.4468	1.1245	14(tie)	D
New Impala	1.2968	2.7480	2	1.2430	1.1919	2	1.0879	0.3401	2	A
One-year old Impala	0.7136	1.5876	12	0.7109	0.8153	11(tie)	0.7098	0.7192	12	C
New Cavalier	0.8499	2.5436	6	0.7880	0.9185	7	0.7775	0.4604	6	C
One-year old Cavalier	0.4441	1.5857	14(tie)	0.4432	1.1940	14	0.4467	1.1952	14(tie)	D
New Cutlass	1.0929	2.3741	3	1.0508	1.0347	3	1.0354	0.3094	3	B
One-year old Cutlass	1.0178	1.6249	5	1.0134	1.1921	5	1.0060	0.2803	5	B
New Accord	0.8522	2.5613	6	0.8231	1.0674	6	0.7571	0.4861	8	C
One-year old Accord	0.7257	1.8162	11	0.7276	0.9207	11(tie)	0.7139	0.6916	11	C
New Camry	0.7691	2.4402	8	0.7430	1.1977	8	0.7769	0.4713	7	C
One-year old Camry	0.7268	1.8285	10	0.7276	0.9172	9(tie)	0.7140	0.6891	10	C
Other new cars	1.3636	2.7362	1	1.3253	1.2447	1	1.1169	0.3387	1	A
Other one-year olds	0.4441	1.7041	16	0.4361	1.9554	15(tie)	0.4058	0.4736	16	D
Marginal Costs ($'000):										
Pinto	6.0528	1.2903		5.2806	0.8853		8.1307	3.4791		
Escort	3.6908	1.6026		3.3075	0.5282		2.5022	2.4504		
Impala	7.5490	1.7878		6.9408	1.1326		6.6748	2.9616		
Cavalier	2.9489	1.3599		3.5198	0.6973		0.5660	1.5727		
Cutlass	7.2688	1.5357		7.0986	1.3174		8.4897	3.8004		
Accord	8.1508	1.2226		6.8482	1.2968		7.7099	3.3729		
Camry	6.0787	0.8892		5.5633	1.2128		6.8623	3.1143		
$\bar{\theta}$ ($'000)	4.9179	3.9413		6.1929	2.7810		22.0702	6.6503		
Market definition	All cars in use			All cars $\leq$ three-years old			All cars $\leq$ two-years old			
% of inequalities satisfied[c]	55%			54%			54%			
# moment restrictions	70			70			70			

[a]Using the asymptotic approximation $Var\hat{\theta} \approx \frac{1}{T}\Sigma_T$, where Σ_T is the finite-sample approximation of the variance-covariance matrix in equation (45).
[b]The α for the outside good has been normalized to 0.
[c]Percentage of the inequalities (equation (10) in the main text) which are satisfied, at the estimated parameter values, and realized prices.

Table 3: Estimated total discounted qualities
Using Model II Results

Car Model	New Quality α_{new}	One-year old Quality α_{used}	Total Discounted Quality TDQ$\equiv \alpha_{new} + \delta * \alpha_{used}$
Pinto	1.020	0.436	1.435
Escort	0.730	0.443	1.151
Impala	1.243	0.711	1.918
Cavalier	0.818	0.444	1.240
Cutlass	1.051	1.013	2.014
Accord	0.823	0.728	1.514
Camry	0.748	0.728	1.441

Table 4: Estimated markups

Car Model	Avg. MSRP ($'000)	Model I	Model II	Model III
Pinto	6.0396	-0.0022	0.1257	-0.3462
Escort	6.6788	0.4474	0.5048	0.6254
Impala	9.2626	0.1850	0.2507	0.2794
Cavalier	8.3163	0.6454	0.5768	0.9319
Cutlass	9.7702	0.2560	0.2734	0.1311
Accord	9.8667	0.1739	0.3059	0.2186
Camry	9.9681	0.3902	0.4419	0.3116

1971 Choice Set

$$\begin{bmatrix} x^{\text{Pinto}}_{new} & (B) \\ x^{\text{Impala}}_{new} & (A) \\ x^{\text{Cutlass}}_{new} & (B) \end{bmatrix} = \begin{bmatrix} 5.6056 & -0.2679 & -0.1925 & -0.2744 & -0.1181 & -0.2054 \\ 4.9729 & -0.2255 & -0.0265 & -0.0377 & -0.0162 & -0.1297 \\ 6.9011 & -0.1141 & -0.1466 & -0.2090 & -0.0900 & 0.0287 \end{bmatrix} \times \begin{bmatrix} 1 & \\ x^{\text{Other new}} & (A) \\ x^{\text{Impala}}_{used} & (C) \\ x^{\text{Cutlass}}_{used} & (B) \\ x^{\text{Pinto}}_{used} & (D) \\ x^{\text{Other one-year old}} & (D) \end{bmatrix}$$

1981 Choice Set

$$\begin{bmatrix} x^{\text{Escort}}_{new} & (C) \\ x^{\text{Impala}}_{new} & (A) \\ x^{\text{Cutlass}}_{new} & (B) \\ x^{\text{Accord}}_{new} & (C) \end{bmatrix} = \begin{bmatrix} 5.5497 & -0.1299 & -0.2202 & -0.1586 & -0.2254 & -0.1373 & -0.2269 \\ 7.2932 & -0.2574 & -0.0690 & -0.1498 & -0.0707 & -0.0430 & -0.0575 \\ 7.8384 & -0.2346 & -0.1011 & -0.1941 & -0.1034 & -0.0630 & -0.0467 \\ 4.8540 & -0.1437 & -0.1554 & -0.1495 & -0.1591 & -0.0969 & -0.0986 \end{bmatrix} \times \begin{bmatrix} 1 & \\ x^{\text{Other new}} & (A) \\ x^{\text{Impala}}_{used} & (C) \\ x^{\text{Cutlass}}_{used} & (B) \\ x^{\text{Accord}}_{used} & (C) \\ x^{\text{Escort}}_{used} & (D) \\ x^{\text{Other one-year old}} & (D) \end{bmatrix}$$

1990 Choice Set

$$\begin{bmatrix} x^{\text{Escort}}_{new} & (C) \\ x^{\text{Cavalier}}_{new} & (C) \\ x^{\text{Cutlass}}_{new} & (B) \\ x^{\text{Accord}}_{new} & (C) \\ x^{\text{Camry}}_{new} & (C) \end{bmatrix} = \begin{bmatrix} 5.4457 & -0.1678 & -0.1574 & -0.1722 & -0.1049 & -0.1722 & -0.1049 & -0.1751 \\ 1.8659 & 0.1261 & 0.0192 & -0.1083 & -0.0660 & -0.1083 & -0.0660 & -0.2138 \\ 8.3937 & -0.3498 & -0.2232 & -0.0370 & -0.0225 & -0.0370 & -0.0225 & 0.0656 \\ 5.5102 & -0.1909 & -0.1635 & -0.1303 & -0.0794 & -0.1303 & -0.0794 & -0.0675 \\ 5.9429 & -0.1674 & -0.1335 & -0.1670 & -0.1017 & -0.1670 & -0.1018 & -0.0822 \end{bmatrix} \times \begin{bmatrix} 1 & \\ x^{\text{Other new}} & (A) \\ x^{\text{Cutlass}}_{used} & (B) \\ x^{\text{Accord}}_{used} & (C) \\ x^{\text{Cavalier}}_{used} & (D) \\ x^{\text{Camry}}_{used} & (C) \\ x^{\text{Escort}}_{used} & (D) \\ x^{\text{Other one-year old}} & (D) \end{bmatrix}$$

Table 5: Equilibrium decision rules
Using Model II Results
Tier in parentheses (see Table 2 for definition).

Table 6: Results from counterfactual experiments
Using Model II results, for 1981 choice set

	Escort (Ford)	**Impala** (GM)	**Cutlass** (GM)	**Accord** (Honda)
Tier (new)[a]	C	A	B	C
Tier (used)	D	C	B	C
Panel I: Baseline results reported figures are *(i)* Output (millions of units) *(ii)* Single-period profits ($billions)				
Panel I: Baseline results				
(i)	0.6011	0.8745	1.8486	0.5271
(ii)	0.0779	0.2295	1.1508	0.0685
Panels II and III: Counterfactuals results reported figures are *(i)* % change in output *(ii)* % change in profits relative to above baseline results				
Panel II: Full commitment results				
(i)	25.79	-2.62	-30.38	19.15
(ii)	164.94	86.99	2.84	202.47
Panel III: Effects from reduced durability in				
Escort				
(i)	338.05	-22.41	-4.71	-67.26
(ii)	1064.03	-41.65	-12.62	-89.70
Impala				
(i)	11.35	87.87	-4.39	6.61
(ii)	22.76	161.81	-11.89	11.89
Cutlass				
(i)	20.36	27.37	34.18	38.89
(ii)	42.98	59.31	0.60	89.99
Accord				
(i)	-19.33	-12.61	-4.36	234.60
(ii)	-35.71	-25.13	-11.91	569.37

[a] as defined in Table 2