Keeping it fresh: Strategic product redesigns and welfare

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A R T I C L E   I N F O

A B S T R A C T

Product redesigns happen across virtually all types of products, yet there is little evidence on the market and welfare effects of redesigns. We develop a model of redesign decisions in a dynamic oligopoly model and use it to analyze redesign activity in the U.S. automobile market. We find automobile model redesigns are frequent despite an estimated average cost around $1 billion. Our estimates also suggest that redesigns lead to large increases in profits and welfare due to the strong preferences consumers have for redesigns. We show that welfare would be improved if redesign competition were reduced, allowing redesign activity to be more responsive to the planned obsolescence channel. The net effect of these changes would reduce total redesigns by roughly 10%, increasing total welfare by roughly 3%. The high valuation that consumers put on newly-designed models drives frequent redesigns and gives automobile manufacturers fairly substantial market power, with a 2-to-1 ratio of firm profits to consumer surplus.

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1. Introduction

Product redesigns happen across virtually all types of products from breakfast cereals to tennis shoes to automobiles, and likely occur with much greater frequency than new variety introductions. For example, we find in the data we use in this paper that redesigns of existing automobile models (e.g., a Honda Civic) occur with twice the frequency of the introduction of entirely new models. Surprisingly, there has been little economic analysis of the decision by producers to redesign existing products and the effects these redesigns have on consumer decisions and overall welfare.

There are a number of factors that may cause producers to redesign existing products. One may be to incorporate new functional technology, upgrading the quality of an existing variety while maintaining brand recognition with consumers. For example, a company may develop a revised formula for their laundry detergent to better clean clothes and introduce a "new and improved" version of their product.[1] A second reason may be to simply update the product's appearance for consumers who value design changes. This would imply that consumers not only value having many variety choices at a given point in time, but also respond positively to dynamic changes in existing varieties, even if function and quality are essentially unchanged. For example, the fashion industry introduces frequent seasonal changes in colors and styling of clothes by brand name designers that have little to do with quality or functionality changes.

Importantly, these redesign decisions have both internal and external strategic implications in the marketplace. Externally, redesign timing of products is a dimension in which a firm may compete with other firms in the marketplace. This is particularly true if consumers strongly value the "new" features that come with redesign, such that newly redesigned products steal market share at the expense of other competitors.

Independent of these external considerations, a main internal consideration for a firm is that a redesigned model will be replacing the firm's own existing variety. This is most important in the case of durable goods, as secondhand sales may significantly erode demand for current production of a product. This erosion creates an incentive for the firm to introduce a redesigned model of the product to limit the competition of secondhand markets with its current product, a phenomenon that has been termed "planned obsolescence."

In this paper, we use a model of strategic redesign decisions by U.S. automobile manufacturers in a dynamic oligopolistic setting to estimate the impact of these external and internal strategic considerations on the redesign decisions and its resulting impacts on the marketplace. We employ a model of dynamic oligopoly that follows Bajari et al. (2007) (hereafter, BBL) in order to model redesign and exit decisions. The estimation procedure allows us to estimate both the structural parameters determining current period demand and profits for each product, but also the dynamic parameters (costs) determin-

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[1] There is also evidence that pharmaceutical manufacturers create redesigns of drugs with new features when the patent expires in order to differentiate from generics.

ing exit and redesign decisions. Because the specification is tied to a structural model, we can also simulate alternative scenarios to understand implications for welfare.

We find that redesigns are a costly activity in the automobile market, averaging about $1 billion in costs. Yet, redesigns are fairly frequent because consumers value redesigns strongly. Model designs become obsolete quickly as demand falls with a model's age, leading to fairly frequent redesigns by automobile firms and almost a 20% gain in a model's market share the year of a new redesign. The incentive to recapture declining market share through a new design is what we call the "obsolescence" motive, and comes through strongly in our estimates. We also find evidence that model redesign decisions are influenced by redesigns of competing models, which we term the "competitive re-design" motive. Based on our structural model estimates, we then simulate an entire set of different combinations of reduced or increased strength of these two forces on redesign activity. We show that welfare would be improved if redesign competition were reduced, allowing redesign activity to be more responsive to the planned obsolescence channel. The net effect of these changes would reduce total redesigns by roughly 10%, increasing total welfare by roughly 3%. The high valuation that consumers put on newly-designed models drives fairly frequent redesigns and gives automobile manufacturers fairly substantial market power, with a 2-to-1 ratio of firm profits to consumer surplus. We also note that we find quite heterogeneous effects across classes of automobiles (e.g., trucks versus cars). While our model and welfare simulations are focused on the new automobile market, we provide some evidence that the gains from redesigns in the new automobile market are an order of magnitude larger than the losses in the secondhand automobile market.

Our analysis relates in important ways to some prior literature. First, there has been a significant number of theoretical analyses of planned obsolescence. Much of the earlier literature concerns the monopolist's choice on durability and pricing of products, assuming that new and used goods are perfect substitutes.[2] This led to some surprising results, such as prices being driven to marginal cost. However, later work shows that these results are not robust to relaxing various modeling assumptions such as perfect substitutability between old and used goods. For example, depending on assumptions, a durable goods producer may redesign a product more frequently than is socially optimal (Waldman, 1993; 1996) or less than is socially optimal (Fishman and Rob, 2000). Likewise, studies come to different conclusions on whether these forces tend to decrease or increase firm profits, or decrease or increase consumer welfare. Surprisingly, these conclusions are ambiguous even though these studies invariably consider the case of a monopolist producer.[3] Thus, our estimates provide some of the very first empirical evidence for many of these theoretically ambiguous effects, including the frequency of redesigns, firm profitability and overall welfare.

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[2] Most point to Swan (1970) and Coase (1972) as the initial papers in this literature. Waldman (2003) and Grout and Park (2005) provide surveys of the literature from fields of economics and marketing, respectively.
[3] An exception is Grout and Park (2005).

There has been a smaller set of empirical studies that have examined the issue of planned obsolescence or related issues connected with secondhand markets for durable goods. Unlike our analysis, however, these studies have been primarily focused on modeling and estimating consumer behavior across the new and secondhand markets, taking introductions of new and redesigned varieties as given. For example, Purohit (1992) estimates how much new automobile model introductions affects prices of secondhand models, while Porter and Sattler (1999) show that the greater the substitutability between the used and new automobile model, the more transactions one sees in the secondhand market, consistent with a view that the secondhand market facilitates vertical product differentiation for consumers. Esteban and Shum (2007) and Chen et al. (2013) build a structural model of a secondhand market of consumers and analyze how much this affects firm profitability by new automobile manufacturers. Finally, Chevalier and Goolsbee (2009) show that consumers are forward-looking and become much more price-elastic in their purchases of a textbook when a new edition in the coming period is likely. This forward-looking behavior reduces the benefits from strategic obsolescence to firms. We view these studies as more complementary than similar, as our focus is on modeling strategic redesign decision by firms. This allows us to focus directly on the internal and external factors that affect this redesign decision and its ultimate effect on profits and welfare.

The papers closest in spirit to our paper are Iizuka (2007), Goettler and Gordon (2011), and Kim (2013). Iizuka (2007) estimates the factors that affect the timing of a new edition of a textbook. The hazard-model analysis finds significant evidence for a planned obsolescence motive, as greater used textbook sales and age of the textbook make a new edition more likely. However, there is no evidence for competitive motives from rival textbooks on the timing of a new textbook. The reduced-form approach by Iizuka (2007) does not allow one to examine how new model introductions affect the dynamic nature of redesign competition or the implications for firm profits and consumer welfare, as does our approach. Goettler and Gordon (2011) estimate a dynamic duopoly model with durable goods for the microprocessor industry. Within their model, firms invest in R&D to have a probabilistic chance of increasing the quality of their product. Investment in their model is similar in nature to our decision to remodel; however, in our setting firms incur a fixed cost to remodel and it occurs with certainty.[4] Kim (2013) also combines a discrete choice model with a two-step approach similar to BBL to analyze the interaction of innovation, production and the used market in the jumbo jet market. She uses the parameter estimates to analyze the welfare effects of governmental subsidies; her

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[4] A second departure of our model with Goettler and Gordon (2011) is that we do not model consumers as forward looking. In contrast to markets where technology is rapidly developing, giving consumers strong incentives to delay until the next model generation, technological improvements are much slower over redesign cycles in the automobile market. Also, the automobile market is a horizontally differentiated-goods one with many varieties available to consumers each period that are nearly functionally identical. As a result, the incentive for consumers to substantially delay purchase of any particular model (out of the many available) in anticipation of that particular model's redesign is likely quite small.

focus is on new products.[5] Our paper differs from these by examining more concretely the relative effects of competitive redesign versus planned obsolescence motives on the timing of redesigned models.

On a final note, our analysis also relates to prior research demonstrating that consumers realize considerable welfare gains from the development of new products (Petrin, 2002) and the introduction of new varieties within product class (Feenstra, 1994; Broda and Weinstein, 2006). While these studies demonstrate the effect of new varieties on welfare, we show that redesigns of existing varieties can likewise be an important source of changes in overall welfare.

Our paper proceeds in the following fashion. In the next section we provide some basic information on our data and the observed patterns of redesign of automobile models. In Sections 3 and 4, we construct a dynamic model of redesign and competition in the U.S. automobile market, and estimate the model's parameters using annual data from 1988 through 2009. Sections 5 and 6 present simulation results from our dynamic model, focusing on the effects of redesign on firm profits and consumer welfare. We also show how various motives for redesign (obsolescence versus redesign competition) affect redesign activity and welfare. Section 7 concludes.

2. Redesigns in the automobile industry: A first look

Before developing a more formal empirical model to examine the motivations and effects of redesigns, this section provides basic information on how automobile manufacturers redesign vehicles, as well as key features of the empirical redesign patterns we see in the data.

We gather much of our annual data on U.S. automobile models from standard sources used by others in the literature. Sales by U.S. automobile models come from *Ward's Automotive Yearbook*, while data on manufacturer-suggested retail prices and physical characteristics by automobile models were obtained from the *MSNAutos* website.[6] Our data span the years from 1988 through 2009, as 1988 was the first year that physical characteristic data are available from *MSNAutos*. Data on redesigns come from *Wikipedia*, which provides comprehensive information on design changes across all automobile models sold in the United States over time, often including narrative details about the nature of the redesigns. Trade journals, such as *Autoweek* and *Motor Trend*, do not have comprehensive information on redesigns, but often report on the introduction of newly redesigned models. We used these to verify the high degree of accuracy of the redesign information available from *Wikipedia*.

Redesigns in the automobile industry allow manufacturers to not only incorporate new technology into the engineering of their vehicle, but also the opportunity to re-style

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[5] Wollmann (2014) likewise examines a related, but different, issue using commercial vehicle data - exit and entry of new models – whereas we focus on redesigns of existing models.
[6] For details see, http://home.autos.msn.com.

its interior and exterior.[7] For example, a recent *Automotive News* article says General Motor's two main concerns with an upcoming redesign of the Camaro is how to reduce its weight to meet fuel efficiency standards and how to come up with new styling that will be as popular as the current model's styling.[8] We focus on redesigns of models rather than minor updates that can occur annually, typically termed "refreshings" or "facelifts".[9] Redesigns receive substantial attention by industry magazines, trade journals, and even popular media, while refreshings receive relatively little attention, even in trade journals. As a result, there is no systematically available data on refreshings and our focus is solely on redesigns.

Redesigns are an involved and costly process. Automobile manufacturers employ teams of engineers and designers that work for years on new redesigns, and which also involve substantial coordination of suppliers, retooling of assembly lines, etc. While redesign cost numbers are closely guarded by automobile manufacturers, anecdotal information suggests that it can be over $1 billion.[10] Our estimates below are quite consistent with this, averaging $1.25 billion over the various classes of automobiles. Thus, redesigns are major economic decisions facing automobile manufacturers.

While redesigns are costly, redesigns of existing automobile models happen with considerable frequency. Table 1 provides a number of statistics by class of vehicle. The age of a vehicle when it is redesigned (Design Age) averages about 6–8 years, with around 70% of all vehicles taking 4–7 years between redesigns. The likelihood that a vehicle will be redesigned in any given year is around 10%. There is clearly some variation in redesign times across class of vehicles. Our analysis will be able to provide evidence on the extent to which various factors (redesign costs versus redesign competition features) explain this heterogeneity.

Our paper is obviously interested in the timing of redesigns and the factors that determine that timing. As an initial investigation into how market share responds to product redesigns, we estimate an event study where the event is defined as a redesign. Fig. 1 plots percentage changes in market shares across cars, trucks and luxury vehicles around a redesign and over various design ages. Panel (a) shows that just prior to a redesign market shares appear to be either constant or slightly decreasing; however, a redesign increases market share by between 20% and 60%, depending on the type of vehicles. Panel (b) of Fig. 1 illustrates that the decline in market shares following a redesign is quite rapid starting for models that are two years old and continues to decline as the vehicle ages.

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[7] Drivetrain changes, such as engines and transmissions, often occur during redesigns. Therefore one obvious motivation for redesigns is to incorporate technological advances in drivetrain components. Knittel (2011) estimates that holding weight and horsepower constant, fuel economy increases roughly 2% per year because of technological improvements.

[8] See http://www.autonews.com/article/20120313/BLOG06/120319962

[9] For example, the 2004 refreshing of the Honda Civic included introducing a new shape for the car's headlights. Other examples of more minor "refreshings" include adding bluetooth technology and introducing new exterior color options.

[10] See http://www.forbes.com/2006/03/31/spring-luxury-cars__cx__dl_0403feat.html

Table 1
Summary statistics.

Body	Class	Redesign fraction	Rival redesigns	Age	Design age	Rivals	Price ($1000s)	Sales (1000s)	$\frac{Miles}{\$}$	$\frac{HP}{Weight}$	Size (m^3)	Engine displace	Exit frac	Total models
Car	LRG	0.131	1.38	3.69	6.05	11.23	19.01	100.54	18.26	54.65	13.63	3.63	0.054	21
	MIDLOW	0.071	0.38	3.99	6.23	8.37	12.56	84.90	22.17	46.45	11.34	2.40	0.130	24
	MIDSPC	0.112	1.38	4.41	7.11	11.54	16.52	42.81	20.33	56.43	10.62	2.90	0.079	25
	MIDUP	0.126	2.33	3.73	6.14	18.12	16.46	114.07	19.86	51.36	11.91	2.69	0.067	43
	SMLLOW	0.099	1.56	3.62	5.50	16.61	9.82	32.65	25.79	44.04	9.41	1.71	0.143	46
	SMLUP	0.122	2.40	3.69	5.97	18.43	11.24	111.08	23.48	46.83	10.45	1.92	0.076	44
Luxury	LUXLOW	0.085	1.67	4.22	6.51	15.67	25.54	32.58	17.80	57.91	12.14	2.93	0.107	42
	LUXMID	0.096	1.48	4.14	6.48	13.26	32.56	32.19	17.41	60.16	12.92	3.59	0.076	29
	LUXSPC	0.062	1.63	4.36	7.06	18.99	41.38	11.36	17.13	73.63	10.77	3.74	0.090	49
	LUXSUV	0.082	0.80	4.48	7.27	8.65	34.17	14.13	11.68	47.19	16.75	4.40	0.061	19
	LUXUP	0.152	1.13	3.44	5.84	7.83	52.89	9.97	15.42	70.76	13.37	4.29	0.033	15
Truck	CUV	0.052	2.44	3.50	5.98	31.81	24.47	58.48	12.65	54.49	14.36	3.05	0.033	37
	PU	0.087	1.55	4.76	8.14	15.15	15.70	185.55	15.72	44.29	17.31	3.97	0.052	28
	SUV	0.071	1.97	4.72	7.53	22.31	20.08	80.49	14.33	47.10	15.13	3.93	0.059	47
	VAN	0.071	2.05	5.81	8.71	25.21	17.98	62.06	15.58	41.88	17.52	3.73	0.083	46

Notes: This table provides summary statistics for our full sample of data on all automobile models sold in the United States from 1994 through 2009. Sales by U.S. automobile models come from Ward's Automotive Yearbook, while data on manufacturer-suggested retail prices and physical characteristics by automobile models were obtained from the MSNAutos website. Data on the timing of redesigns were hand-collected from Wikipedia. Variable definitions are as follows. *Redesign Fraction* is the average fraction of models redesigned annually, while *Rival Redesigns* is the average number of redesigns by rival models annually. *Age* is the average age of a model in a given year, whereas *Redesign Age* is the average age that a model is redesigned. *Rivals* is the average number of models annually. *Price* is the average manufacturer's suggested retail price (MSRP) in thousands of dollars, while *Sales* is the annual number of automobiles sold in thousands. *Miles*/$ is the average miles-per-dollar, *HP/weight* is the average horsepower per weight of the car in thousands of pounds, *Size* is the average interior volume of the automobile in cubic meters, and *Engine Displace* is the swept volume of all the pistons inside the cylinders of the engine in cubic inches. *Exit Frac* is the average fraction of models that annually exit the market, while *Total Models* is the total number of models over the entire sample. Summary statistics are reported by class of models within a general vehicle body following *Ward's* definitions. For cars LRG denotes large, MID denotes midsize and SML denotes small. Vehicle class additionally denotes market segment where LOW denotes low end, SPC denotes specialty and UP denotes high end. Lastly, trucks include compact utility vehicles (CUV), pickups (PU), sport utility vehicles (SUV) and vans (VAN).
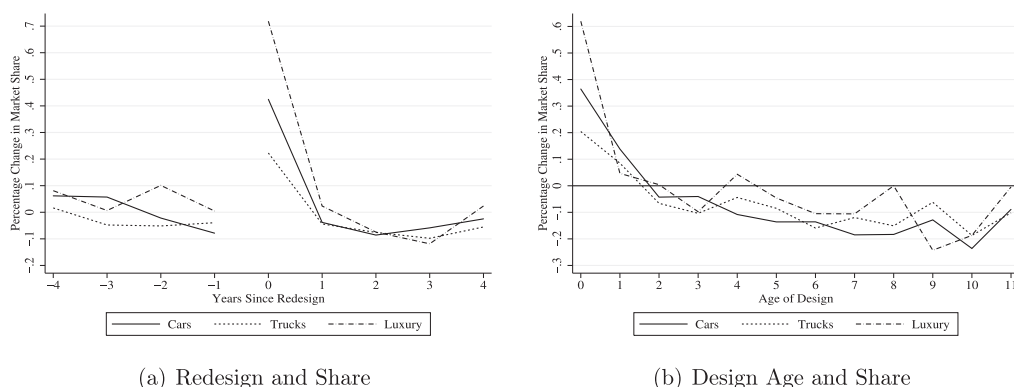
(a) Redesign and Share

(b) Design Age and Share

Fig. 1. Design lifecycle.

A potentially confounding factor explaining these market share changes around a redesign is advertising patterns. Increased advertising expenditures by automobile manufacturers and dealers to promote redesigns could partially or even largely be responsible for these market share changes. If so, this may or may not change the welfare implications from such market share changes depending on one's view of the effect of advertising on consumer behavior.[11] Systematic data on advertising by car models is not available to us and we could find no systematic analysis of this issue with the exception of Nichols (1998), which finds no evidence of a statistically significant correlation between redesigns and advertising expenditures by U.S. automobile models for the period from 1984 to 1990.

We now turn to developing a structural dynamic model of the automobile market, where we focus on the manufacturers' strategic decisions to redesign their models to maximize current expected profits. This will allow us to then separately identify the importance of various forces affecting the redesign decision and the resulting implications for profits and welfare.

3. The dynamic model and estimation of static parameters

In this section, we explain the dynamic framework we use to examine the competition amongst models of automobile firms, with particular focus on the decision to redesign a model. Our framework follows BBL and Sweeting (2013) closely. However, the auto industry is made up of a handful of firms overseeing a number of brands that each produce a set of models (i.e., multi-product firms), which requires discussion before detailing our framework further.

Multi-product firms can create interdependencies on the demand side and on the cost side. On the demand side, a firm will consider cannibalization effects across its models

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[11] For example, if advertising simply provides information to consumers, then this does not affect the welfare implications we draw in this paper, except for taking into account the additional advertising costs that were incurred by the manufacturers and dealers to better inform consumers.

as it makes pricing decisions. We address this by calculating optimal prices within a multi-product setting. Thus, our measure of static profits account for non-zero cross-price elasticities within an auto maker's set of products.

Cost-side interdependencies could occur with production costs or redesign costs, and would be more difficult to control for in our framework. However, car manufacturers primarily have separate production lines (often in different locations) for each of their models. Likewise, anecdotal evidence suggests that each model has its own unique redesign team. There are examples of models that share a common "platform". However, we do not find any significant effect of common platforms on the timing of a model's redesign.

Given this discussion, we proceed by treating each model (j) as the equivalent of a separate forward-looking enterprise maximizing its own dynamic payoffs while taking into account static demand interdependencies. Each enterprise makes decisions at times $t = 1, \ldots, \infty$ of which actions to take in order to compete in the oligopolistic market given current states. We consider two different types of states that firms face - ones internal to the firm, such as the obsolescence motive, and ones external to the firm. The first type of internal state we account for is the newness of the model's design (n_{jt}). We account for this through a variable that denotes the age of a model in years. It is important to include this state variable so that our obsolescence state variable (discussed next) is capturing obsolescence motives, not consumers' possible preferences for more recent designs. The second type of internal state is the obsolescence state variable (o_{jt}), which we account for by constructing the total stock of units of the current model sold in previous periods: $Stock_{jT} = \sum_{t=1}^{T} \mathbb{K}(Design_{jt} = Design_{jt-1}) * q_{jt-1}$. Theory suggests that a greater stock of the current model will give the firm greater incentive to redesign. Finally, we include state variables that capture the competitive redesign forces that are external to a firm. Redesigns by rival firms may steal market share from the firm's own model. We proxy for these competitive redesign states (c_{jt}) using the average age of competing models, as well as the total redesigns of models by competitors since the model's last redesign within vehicle class in a given year.[12] We note that we will be primarily interested in "redesign competition" in our analysis (i.e., firms timing redesigns to compete with redesigns of competing models), not the underlying market structure of competition. In other words, we will not be examining in this paper what would happen if the market goes from many competitors to a single monopolist. The full set of states in period t is denoted as $\psi_{jt} = \psi_{jt}(n_{jt}, o_{jt}, c_{jt}) \in S \subset \mathbb{R}^L$.

To be clear about the evolution of our state variables given actions, notice the actions $a_{jt} \in A_j$ available to firms in period t are: 1) do nothing, 2) redesign, or 3) exit. Suppose in period t that firm f takes no action to change a model j whose design is 3 periods old. In $t + 1$ the age of their model increases by one to 4, and stock increases by the number of units that were sold in t. If this same firm decided to release a redesign of

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[12] To be explicit, total redesigns faced by model j in period T is defined as: $Total\ Redesigns_{jT} = \sum_{t=1}^{T} \mathbb{K}(Design_{jt} = Design_{jt-1}) * \sum_{i \notin j} Redesign_{it}$.

this model next period, in $t + 1$ the age of the model (Age_{jt}) is reset to unity and stock ($Stock_{jt}$) is reset to zero. The competitive redesign states evolve according to the actions taken by firms in the same product class. For example, if no models of compact cars are redesigned in $t + 1$ the average age of competitors ($AgeComp_{jt}$) increases by one, and total competitor redesigns do not change ($Total\ Redesign_{jt} = Total\ Redesign_{jt-1}$). Firms that exit receive a value to scrap their model, and cannot reenter the market.[13]

Model j's profit in t is a function of current states, private information, and actions, which we denote as $\Pi_{jt}(\boldsymbol{a}_t(\boldsymbol{\psi}_t, \boldsymbol{\nu_t}), \boldsymbol{\psi}_t, \nu_{jt})$. Firms dynamically optimize the present value of current and future profits,

$$V_j(\boldsymbol{\psi}; \boldsymbol{a}; \theta) = \mathbb{E}\left[\sum_{t=1}^{\infty} \beta^{t-1} \Pi_{jt}(\boldsymbol{a}_t(\boldsymbol{\psi}_t, \boldsymbol{\nu_t}), \boldsymbol{\psi}_t, \nu_{jt}; \theta) \Big| \boldsymbol{\psi}_t; \theta \right],$$

where β is a common discount factor shared by firms, and $\boldsymbol{a}_t$ denotes the set of actions taken by the firm and its competitors in period t, which depends on the accompanying set of states $\boldsymbol{\psi}_t$ and private information shocks $\boldsymbol{\nu_t}$.[14] Our goal is to estimate the vector θ that rationalizes observed firm behavior. This vector is denoted as $\theta = [\theta_R, \theta_X, \theta_P]$, where the parameters θ_R, θ_X and θ_P represent the cost of redesign, exit scrap value and a private value parameter, respectively.[15]

To estimate the dynamic parameters, we follow the methodology developed by BBL, which proceeds in three steps. First, we estimate static behavior, which includes the estimation of parameters determining current-period profits and the optimal policies firms follow when taking actions. Second, we construct value functions by forward simulating static markets using policy functions to transition between states.[16] Third, we perturb the policy rules and resimulate the markets in order to estimate the parameters that rationalize our observed market outcomes. In the following sections, we provide more detail on the three steps we use to estimate the parameters of the model.

3.1. The static demand model and the effects of redesigns

To estimate the static effects of redesign on market share and profits for individual automobile models, we follow the standard discrete choice techniques described in Berry

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[13] In what follows we make the simplifying assumption that firms do not form expectations about the exit of their competition. We assume that, in expectation, a firm presumes their competitors will redesign and produce according to their optimal policies for as long as it remains in the market. This is an important assumption since all states and actions are interlinked across all producers. This assumption is equivalent to one where firms expect an exiting model to be replaced by an identical model. Thus, we are not capturing any extensive margin effects on competition.

[14] Private information shocks in this setting could include changes to consumers' preferences with respect to the firm's products, new design ideas for products arising from the firm's design team, or changes in managerial or productive efficiency in the firm's personnel that are only known to the firm.

[15] In the following, we will be explicit about the role of each parameter and the model, but for now it suffices to introduce the notation.

[16] See Kalouptsidi (2014) for an example where one uses observed data on secondhand sales to estimate value functions directly. We do not pursue this here because newly redesigned models are inherently not available in a secondhand market.

(1994) for specifying the demand structure for automobiles. In particular, assume that consumer i makes a discrete choice over automobiles $j \in \mathfrak{J}_g$, nested by automobile class $g = 0, 1, \ldots, G$, to maximize her utility,

$$
\begin{aligned}
u_{ij} &= x_j \mu - \alpha p_j + \xi_j + \zeta_{ig} + (1 - \sigma)\epsilon_{ij} \\
&= \delta_j + \zeta_{ig} + (1 - \sigma)\epsilon_{ij},
\end{aligned}
$$

where ϵ_{ij} is an i.i.d extreme value random variable. The common group (automobile class denoted by g) demand parameter ζ follows a distribution depending on $\sigma \in [0, 1]$. Since ϵ is an extreme value random variable, $\zeta + (1 - \sigma)\epsilon$ is also an extreme value random variable. Characteristics, price, and unobservables of product $j \in \mathfrak{J}_g$ are denoted as x_j, p_j and ξ_j, respectively.

Under the extreme value assumption of ϵ, market share for product j is,

$$
s_j(\delta, \sigma) = \overline{s}_{j/g} \overline{s}_g = \frac{e^{\frac{\delta_j}{1-\sigma}}}{D_g^\sigma \sum\limits_g D_g^{(1-\sigma)}} \tag{1}
$$

where $D_g \equiv \sum_{j \in \mathfrak{J}_g} e^{\frac{\delta_j}{1-\sigma}}$. Assume the outside good represents the option to not buy a new automobile. Normalizing $\delta_0 = 0$ and $D_0 = 1$ implies $s_0(\delta, \sigma) = \frac{1}{\sum_g D_g^{(1-\sigma)}}$. Given this model of demand, Berry (1994) shows the demand parameters can be estimated as,

$$
ln(s_{jt}) - ln(s_0) = x_{jt}\mu - \alpha p_{jt} + \sigma ln(\overline{s}_{j/gt}) + \xi_{jt}. \tag{2}
$$

We address the endogeneity of price and nest share as Berry et al. (1995) suggest, drawing instruments from the characteristics of a model's competitors and competing models produced by the firm.

A multi-product firm f with models $j \in \mathfrak{J}_f$ will set prices in order to maximize profits across their models taking into account the possibility of cannibalization. Static profits are calculated each period from the solution of the nested-logit demand discussed above, and assumed Bertrand competition. Static profits each period are,

$$
\pi_{ft}(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{\psi}_t, \xi_t; \sigma, \alpha) = \sum_{j \in \mathfrak{J}_f} (p_{jt} - mc_{jt}) M s_{jt}(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{\psi}_t, \xi_t; \sigma, \alpha),
$$

where M is market size, defined as the total number of households in the US, and mc_{jt} represents firm-specific marginal costs. Given these assumptions, the price set by firms for each model must satisfy the first-order condition

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s_{jt}(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{\psi}_t, \xi_t; \sigma, \alpha) + \sum_{k \in \mathfrak{J}_f} (p_{kt} - mc_{kt}) \frac{\partial s_{kt}(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{\psi}_t, \xi_t; \sigma, \alpha)}{\partial p_{jt}} = 0.
$$

Moral and Jaumandreu (2000) describe a closed form solution to this model where multi-product firms maximize profits across varieties facing a nested-logit demand. They

demonstrate that the optimal firm pricing rule for each model is,

$$p_{jt} = mc_{jt} + \frac{1-\sigma}{1-\sigma\bar{s}_{j/g\,t}}\left(\frac{1}{\alpha} + \frac{(1-\sigma)\sum_{r=1}^{J_f}\frac{s_{rt}}{\alpha(1-\sigma\bar{s}_{r/g\,t})}}{1-(1-\sigma)\sum_{r=1}^{J_f}\frac{s_{rt}}{1-\sigma\bar{s}_{j/g\,t}}}\right),$$

for all models j in the set of models produced by the firm J_f at time t.

We take this specification to our data and Table 2 provides our estimates of the determinants of market share from our nested-logit discrete choice demand specification. Our empirical approach is to use a full set of model age dummies to capture the difference in utility across the typical vehicle's age profile. That is, we allow the unobserved quality terms, ζ_{ig}, to non-parametrically vary over the lifecycle of vehicles, and assume this variation captures the loss/gain in utility from the design age of the model. This requires an assumption regarding what vehicle features we want to hold constant. For example, we could ask what is the value of product redesigns holding constant variables that we typically use to describe vehicles, such as horsepower, fuel economy, etc. Alternatively, we may want to allow changes in these product attributes to be subsumed in the model-age dummy variables, since changes in these characteristics may occur during redesigns. We show results under both assumptions and note that our main empirical results are robust to the demand specification.

Columns 1 through 4 provide OLS estimates of relative market share. In the first column, we specify a base specification that only includes the price of the model and the market share of the model within its own group. The price term is negative and statistically significant, even without yet controlling for its possible endogeneity, while the group market share is positive and statistically significant.

In Column 2, we add observable physical attributes of the model—fuel efficiency, horsepower relative to weight, size, and engine displacement to the base specification,[17] while column 3 adds the redesign and age dummies for the model to the base specification (without the observable physical characteristics). Age dummies control for the newness of a model's design. Column 4 adds both observable attributes and the redesign and age variables. Importantly, the coefficients on the physical attributes are virtually unaffected by inclusion of the redesign and age variables, and likewise, the coefficient on the redesign variable and qualitative pattern of coefficients on the age dummies are hardly affected by inclusion of the physical attributes of the vehicles. This highlights an important point— much of the effect of redesigns on market shares and profits does not stem from changes in physical (functional) attributes that we can measure consistently across models, such as size or fuel efficiency. Thus, consistent with anecdotal evidence in the media discussed in Section 2, redesigns appear to be appropriately modeled as significant discrete changes

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[17] As in Berry et al. (1995), we define fuel efficiency as $\frac{Miles}{\$}$ and horsepower to weight as $\frac{HP}{Weight}$. Size is $length \times width \times height$ in cubic meters. The preceding serve as measures of efficiency, acceleration, and size.

Table 2
Market share regressions.

Characteristics	$ln(s_{jt}) - ln(s_0)$						
	OLS				IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price ($1000 *in'85*)	−0.044***	−0.044***	−0.045***	−0.045***	−0.078***	−0.048***	−0.079***
	(0.004)	(0.006)	(0.004)	(0.006)	(0.011)	(0.004)	(0.011)
$log(s_{j/g})$	0.815***	0.823***	0.808***	0.814***	0.413***	0.423***	0.391***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.076)	(0.063)	(0.075)
Miles/$		0.015**		0.014**	0.026***		0.024***
		(0.007)		(0.006)	(0.008)		(0.007)
$\frac{HP}{Weight}$		0.005		0.004	0.026***		0.023***
		(0.004)		(0.004)	(0.007)		(0.006)
$log(Size)$		2.070***		2.000***	1.771***		1.574***
		(0.267)		(0.268)	(0.389)		(0.395)
$log(Engine\ displacement)$		−0.461***		−0.387**	0.312		0.502*
		(0.150)		(0.154)	(0.258)		(0.265)
Redesign			0.172**	0.159**		0.423***	0.376***
			(0.071)	(0.064)		(0.073)	(0.077)
Age = 1			0.108	0.235**		0.207*	0.496***
			(0.095)	(0.102)		(0.118)	(0.139)
Age = 2			0.199**	0.329***		0.448***	0.723***
			(0.083)	(0.092)		(0.114)	(0.137)
Age = 3			0.174**	0.316***		0.397***	0.689***
			(0.083)	(0.092)		(0.112)	(0.135)
Age = 4			0.183**	0.341***		0.398***	0.698***
			(0.083)	(0.091)		(0.113)	(0.134)
Age = 5			0.194**	0.344***		0.412***	0.695***
			(0.081)	(0.090)		(0.112)	(0.134)
Age = 6			0.182**	0.322***		0.364***	0.640***
			(0.079)	(0.089)		(0.106)	(0.131)
Age = 7			0.115	0.265***		0.268***	0.553***
			(0.076)	(0.088)		(0.101)	(0.126)
Age = 8			0.079	0.265***		0.207**	0.484***
			(0.075)	(0.083)		(0.097)	(0.116)
Age = 9			0.011	0.194**		−0.006	0.255**
			(0.076)	(0.085)		(0.101)	(0.115)
R^2	0.709	0.756	0.711	0.759	0.609	0.602	0.607
N	4831	4831	4831	4831	4831	4831	4831

Note: Results from nested logit estimates of market shares. *Age* is the number of years since the model's last redesign and *Redesign* is an indicator for a current redesign. *Price* is MSRP in $1000s. Additionally, we control for vehicle characteristics including horsepower (HP) relative to *Weight*, *Size*, *Displacement*, and *Miles* drivable per dollar. IV regressions address price endogeneity with Berry et al. (1995) instruments. Standard errors clustered by model in parentheses, * $p< 0.10$, ** $p< 0.05$, *** $p< 0.01$.

in the aesthetic design and styling of the model, and independent of changes in the functional attributes of a model (which can vary annually).

Our OLS specifications display good fit of the data (R^2 from 0.71 to 0.76), with many of the variables statistically significant and expected signs. With respect to physical attributes, the estimates suggest that larger, more efficient, and higher horsepower vehicles receive larger market shares. The age coefficients are estimated effects relative to models

that are 10 years or older. A major focus for our paper is the effect of a redesigned pre-existing model, which is the sum of the coefficient on *Redesign* and the dummy variable for $Age =1$.[18] Our estimates suggest that the initial year of a new redesign sees about a 30% larger market share than the excluded group (models ten years old or older), and is significantly larger than any other year of a model's life. The age-effect profile of market share shows a noticeable drop after the initial redesign year and then another fall after year six.[19]

In Columns 5 through 7 of Table 2 we provide 2SLS estimates of the same specifications in Columns 2 through 4. As expected, the coefficient on price becomes larger in magnitude after controlling for endogeneity. In addition, all of the physical attribute characteristics are also statistically significant and accord with findings by previous studies and our intuition. Most notably, the coefficient on the horsepower variable is now significantly positive. Controlling for endogeneity also has substantial impacts on our estimated effects of redesign and age of a model on its relative market share. Their coefficient estimates are much larger than with OLS, and both are now statistically significant at the 1% level. The initial year of a new redesign sees about a 90% larger market share than the excluded group, which falls to about 70% larger than the excluded group in years two through five, and then falling again after year five. The large coefficient on *Redesign* (using column 7 estimates) indicates that the initial market share of a newly-redesigned model is almost 38% greater than the initial market share of a new entrant. Fig. 2 provides a convenient translation of these age and redesign coefficients into market shares (and associated dollar figures) by age of the model relative to year four of a model. As shown in the figure, a newly redesigned model has a market share that is about 20% higher in its initial year than the following years two through six, everything else equal. Market share then falls off rapidly after year six.

As in any modeling exercise, the BBL-based framework we use has a number of assumptions for tractability, some of which may be more concerning for the issue we examine. In particular, estimating static demand means we are not allowing for the possibility of forward-looking consumers who might time the market in anticipation of redesigns, as in Gowrisankaran and Rysman (2012) and Goettler and Gordon (2011). Gowrisankaran and Rysman (2012) model a market (digital camcorders) where technology is leading to

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[18] In contrast, the coefficient on the dummy variable for $Age=1$ is the market share of a new entrant model relative to the excluded group. We have also estimated a more flexible model where we have separate year effects for entrants and redesigns, but we cannot reject equality for age two and higher ages. Therefore, we report the more parsimonious specification.

[19] Our age effects are similar in nature to the specification in Chevalier and Goolsbee (2009), which allows utility for a textbook to fall with the probability of a new edition being released within the next year. If consumers in the automobile market expect future redesigns to lower the resale value of their new car purchase in the current period, then the more likely is a redesign, the lower the utility a consumers will get from the purchase. We note that while this does not affect the interpretation of our age effects, we discuss the empirical evidence of these secondhand market effects in Section 7. In addition, the market for automobile and textbooks likely differ in one key respect: in the market for textbooks, the difference in the quality of new editions, compared to the previous version, is likely to be small. In contrast, consumers in the automobile market appear to value the added features in newer versions considerably.
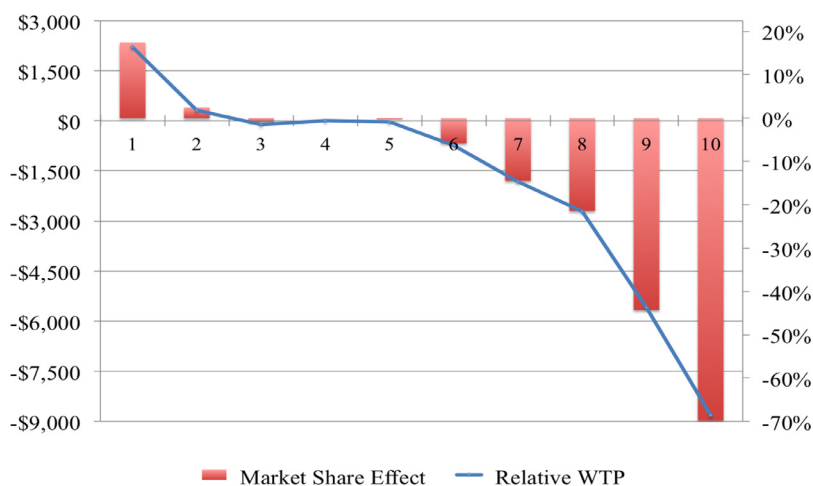
Fig. 2. Estimated age effects from demand model.

rapid quality and functional improvements, which likely means much larger incentives for consumers to delay purchases than in the more mature automobile market where functional changes evolve much slowly over redesign cycles. While Gowrisankaran and Rysman (2012) model a rich dynamic demand side of the market, for tractability reasons, they assume the supply side is one where models and their characteristics arrive according to an exogenous process. In contrast, we make the alternative tractability assumption that the supply side is comprised for forward-looking firms in order to explore their dynamic re-design decisions. Goettler and Gordon (2011) examine a homogeneous market (computer microprocessors) where it is likely that consumers have strong incentives to "time the market" because of rapidly evolving quality and functional improvements. We think this is likely less of an issue in the automobile market where technological or styling changes are not nearly as rapidly changing or dramatic. In addition, a recent survey by AutoTrader.com finds that the large majority (79%) of shoppers "would rather take advantage of a good deal on the current model instead of delaying their purchase for the newest design."[20] Finally, our annual data makes this less of an issue than if we had more high-frequency data.

A second limitation is that we are not modeling the secondhand market for automobiles, except to the extent that secondhand sales of any pre-existing models are accounted for in our specification as part of the consumer's "outside" option in the demand specification. Modeling a richer secondhand market option in a detailed fashion in this framework is likely to be quite complicated and goes beyond this paper's analysis. Some have suggested that the stock of the model should be in our demand estimation directly as it controls for how much of a secondhand market from previous sales is competing with

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[20] See http://press.autotrader.com/2013-04-11-New-Car-Shoppers-Would-Rather-Get-A-Better-Deal-On-A-Current-Model-Than-Delay-Purchase-For-A-Redesign.

the current year's sales. The prediction would be that greater prior sales of this current generation of the model will lower current-period market share. In Table B.2, we explore market share estimates when we include a stock term or, more flexibly, four periods of lagged sales in our 2SLS specification. The stock variable has a positive coefficient in these regressions. We believe this result is because the stock variable is also proxying for the unobserved quality of the current generation's design, which affects both past and current sales in the same direction. When we include lagged sales, we continue to get a positive coefficient on last period's sales (presumably due to the autocorrelation in sales), but negative coefficients for later lags. We believe the negative coefficients on later lags are capturing obsolescence motives. However, this specification is admittedly poorly identified (as we can see from the positive and insignificant coefficient on price), which makes it intractable to use in the rest of our analysis. Importantly, the inclusion of stock or previous-period sales terms does not have any qualitative impact on the redesign coefficient or the general pattern of the age variables.

Given this discussion, we use the 2SLS estimates in Column 7 of Table 2 as our preferred model for estimating the static effects of redesign activity on relative market shares for a given history of redesigns in the market. In order to understand how the history of redesigns evolves dynamically, we next specify and estimate the policy functions for redesign and exit decisions of models. Then our third step is to use our estimated static market share model and optimal policy functions to estimate the dynamic parameters governing these decisions in the following section.

3.2. Optimal policy functions

3.2.1. The redesign decision

We estimate the probability that a model will be redesigned next period with the following logit specification,

$$R_{jt+1} = \gamma_d d_{jt} + \gamma_c c_{jt} + \gamma_o o_{jt} + \epsilon_{jt}^R.$$

Our specification hypothesizes that the probability of redesign next period (R_{jt+1}) depends on the newness, obsolescence, and competitive motives for redesign – the state variables in our model.[21] The newness effect is proxied by the age of the model. Obsolescence motives are captured by the stock of previous production of the model. Competitive redesign motives are captured by the total redesigns by competitors since the model's last redesign, as well as the average age of competitors. To provide as much flexibility as possible to fit the redesign patterns we observe in the data, we also examine specifications with interactions between state variables and higher order terms.

Table 3 displays the results of various specifications of our redesign policy model, where we introduce additional terms sequentially. We start in Column 1 of Table 3 with simply a

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[21] Our redesign policy function specification is also similar to Iizuka (2007) who estimates a hazard model for redesigns in the textbook market.

Table 3
Redesign policy estimates.

Controls	Logit estimates of Pr[Redesign=1]						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.131***	0.117***	0.107***			0.165***	0.987***
	(0.034)	(0.035)	(0.033)			(0.036)	(0.124)
Age^2							−0.050***
							(0.009)
$Age = 2$				−3.103***	−3.161***		
				(0.456)	(0.468)		
$Age = 3$				−1.472***	−1.544***		
				(0.324)	(0.336)		
$Age = 4$				−0.611**	−0.685***		
				(0.253)	(0.262)		
$Age = 5$				0.164	0.088		
				(0.242)	(0.252)		
$Age = 6$				0.485**	0.428*		
				(0.242)	(0.253)		
$Age = 7$				0.376	0.330		
				(0.262)	(0.269)		
$Age = 8$				0.052	0.012		
				(0.279)	(0.288)		
$Age = 9$				0.229	0.167		
				(0.307)	(0.308)		
$Total\ redesigns$		0.044***	0.029**	−0.007	−0.001	0.054***	0.125***
		(0.014)	(0.013)	(0.012)	(0.013)	(0.014)	(0.040)
$Total\ redesigns^2$							−7.262***
							(0.662)
$\overline{AgeComp}$		−0.050	−0.053	−0.071	0.087	0.203***	0.867**
		(0.056)	(0.055)	(0.058)	(0.061)	(0.069)	(0.347)
$\overline{AgeComp}^2$							−0.097*
							(0.050)
$Stock$			0.064***	0.049***	0.058***	0.210***	0.636***
			(0.019)	(0.015)	(0.017)	(0.040)	(0.108)
$Stock \times Age$						−0.019***	−0.065***
						(0.005)	(0.018)
$Stock \times Age^2$							0.003***
							(0.001)
$Stock \times \overline{AgeComp}$						0.001	−0.188***
						(0.017)	(0.049)
$Stock \times \overline{AgeComp}^2$							0.026***
							(0.007)
Group FEs	No	No	No	No	Yes	Yes	Yes
R^2	0.032	0.040	0.052	0.124	0.138	0.082	0.133
N	4514	4514	4514	4514	4514	4514	4514

Note: Results from logit estimates of the redesign policy function. *Age* is the number of years, *Total Redesigns* are the total redesigns by competitors and *Stock* are the total sales since the model's last redesign. *Age-Comp* is the average age of the model's competitors current design. Standard errors clustered by model in parentheses, * $p< 0.10$, ** $p< 0.05$, *** $p< 0.01$.

constant term and the age of the model. We hypothesize that automobile manufacturers will focus their redesign efforts on older models. The coefficient on age is positive and statistically significant at the 1% significance level.

In Columns 2 through 3, we sequentially introduce the newness effects, the effects from competitive redesign motives, and the effects from obsolescence motives, respectively. The coefficients on these variables have the expected sign and are statistically significant. Older models and ones with a greater stock of previous production (even after controlling for age of model) are more likely to introduce a redesign in the coming period. This is consistent with the newness and obsolescence motives. The younger the average age of, and the more redesigns by a model's competitors, the more likely a model will redesign, providing evidence for a competitive redesign motive.

Columns 6 and 7 add various interaction and higher-order terms of our state variables. All of these additional terms are statistically significant, suggesting non-linearities in how the state variables affect the probability of a model's redesign, and also nearly doubling the pseudo-R^2. These final columns add group fixed effects, which also increases the pseudo-R^2, but has hardly any quantitative effect on our estimates. Importantly, there is evidence that all three state variables (newness, competitive redesign, and obsolescence) and their interactions are important for the redesign policy function. The independent effects of model age and stock along with their non-linear and interaction terms are statistically significant at the 1% level. The competitive redesign motive effects are also of the expected sign and statistically significant at the 1% level, along with most of their interactions with other variables.[22]

We use Column 7 estimates as our optimal redesign policy function for the dynamic forward simulations we undertake below. To better interpret the effects of our key state variables on the redesign decision from the estimated coefficients in Column 7, we examine how the predicted redesign probability as a state variable varies. Fig. 3 fits a locally-weighted scatterplot smoothing (lowess) curve through the predicted probabilities of redesign for each of the three main state variables – model's age, stock of past production, and competitors' average age. In general, we see that older models with higher stock are significantly more likely to redesign.[23] Likewise, the obsolescence motive effect on the redesign decision is clear, as higher stock increases the probability of redesign. The competitive redesign motive effects (seen in Panel (c) of 4) are more complicated. Generally, models are more likely to redesign as their competition ages. There are, however, important competitive responses where the probability of a model redesigning falls as their competition continues to age. These nonlinearities are intuitive, and necessitate our use of higher order terms and interactions.

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[22] One potential concern is that the sharing of a common production platform between models may artificially drive redesign timing for these models. While a significant number of models share platforms, we do not find any statistical evidence that our coefficient estimates in the redesign policy function differ between models that share a common production platform and models that do not.

[23] This effect flattens out or reverses for very old models, but this is based on a small handful of van or truck models that rarely remodel.

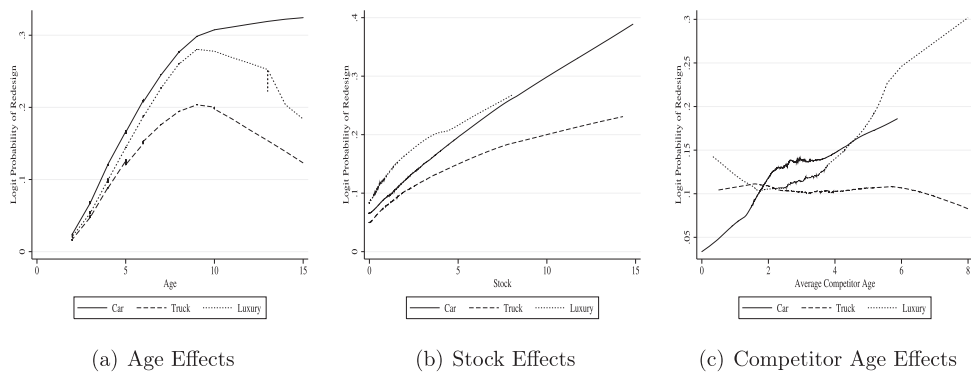(a) Age Effects   (b) Stock Effects   (c) Competitor Age Effects

Fig. 3. Predicted probability of redesign. Notes: Each panel displays how the predicted probability of redesign changes for different values of the state variables based on coefficient estimates from Column 7 of Table 3. Rather than show a scatter plot of predicted probabilities for all observations in our sample we fit a curve through them using a locally-weighted scatterplot-smoothing (lowess) procedure.

3.2.2. The exit decision

In a similar fashion we estimate the probability that the model will exit the market (i.e., discontinue the model) as,

$$X_{jt+1} = \phi_d d_{jt} + \phi_c c_{jt} + \phi_o o_{jt} + \phi_x ln(\bar{s}_{j/g}) + \epsilon_{jt}^X.$$

We specify exit as a function of the same state variables as our redesign specification and report our estimation results in Table 4. We see that the newness effect roughly works in the same direction on a firm's exit decision as it does for the redesign decision—the older the model, the more likely it will exit the market completely. There is evidence that redesign competition affects the exit decision as well. As seen in Column 3, having older competitors makes exit less likely and a greater number of redesigns in the current period lowers the exit probability. Once we include interactions and vehicle group fixed effects (Column 7) statistical significance of the many individual interaction terms for these effects are a bit below standard confidence levels. The obsolescence motive effects on exit decisions and their interactions with the other states work in the opposite direction from that in the redesign policy function. Models with high stocks of previous production are more likely to redesign, but less likely to exit. This is due to the correlation of stock with the success of a model. Maintaining the accrued brand recognition of a high-stock model is likely worth an investment in redesign, rather than scrapping the model altogether through exit. As with the redesign policy function, we use Column 7 estimates for our optimal exit policy function for the dynamic forward simulations we describe next. Similar to Fig. 3 for the redesign policy function, Fig. 45 displays the effect of a model's age, stock of vehicles, and competitor age effects on the probability of exit for various types of vehicles.

Table 4
Exit policy estimates.

Controls	Logit estimates of Pr[Exit=1]						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.129***	0.143***	0.136***			0.110***	0.331***
	(0.029)	(0.029)	(0.028)			(0.025)	(0.057)
Age^2							−0.013***
							(0.003)
$Age = 1$				−3.805***	−3.146***		
				(0.507)	(0.532)		
$Age = 2$				−1.979***	−1.363***		
				(0.301)	(0.323)		
$Age = 3$				−1.115***	−0.608**		
				(0.247)	(0.276)		
$Age = 4$				−0.832***	−0.425		
				(0.236)	(0.263)		
$Age = 5$				−0.463**	−0.170		
				(0.234)	(0.260)		
$Age = 6$				−0.170	0.075		
				(0.230)	(0.257)		
$Age = 7$				−0.265	−0.114		
				(0.257)	(0.273)		
$Age = 8$				−0.817**	−0.781**		
				(0.340)	(0.354)		
$Age = 9$				−0.250	−0.293		
				(0.316)	(0.348)		
Total Redesigns		0.026	0.012	−0.021	0.042**	0.070***	0.104**
		(0.016)	(0.016)	(0.016)	(0.018)	(0.017)	(0.040)
Total Redesigns^2							−0.003
							(0.002)
$\overline{AgeComp}$		−0.324***	−0.337***	−0.329***	−0.098	−0.095	0.321
		(0.074)	(0.075)	(0.070)	(0.097)	(0.105)	(0.451)
$\overline{AgeComp}^{\,2}$							−0.058
							(0.067)
Stock			0.063***	0.064***	0.095***	0.080	0.190
			(0.020)	(0.019)	(0.021)	(0.054)	(0.135)
Stock × *Age*						−0.005	−0.040***
						(0.004)	(0.010)
Stock × Age^2							0.002***
							(0.000)
Stock × $\overline{AgeComp}$						0.018	0.048
						(0.012)	(0.088)
Stock × $\overline{AgeComp}^{\,2}$							−0.007
							(0.014)
$log(s_{j/g})$	−0.733***	−0.761***	−0.821***	−0.866***	−1.007***	−0.986***	−1.004***
	(0.055)	(0.050)	(0.054)	(0.059)	(0.072)	(0.069)	(0.071)
Group FEs	No	No	No	No	Yes	Yes	Yes
R^2	0.180	0.197	0.202	0.238	0.287	0.263	0.273
N	5443	5443	5443	5443	5443	5443	5443

Note: Results from logit estimates of the exit policy function. *Age* is the number of years, *Total Redesigns* are the total redesigns by competitors and *Stock* are the total sales since the model's last redesign. *AgeComp* is the average age of the model's competitors current design. Standard errors clustered by model in parentheses, * $p<$ 0.10, ** $p<$ 0.05, *** $p<$ 0.01.

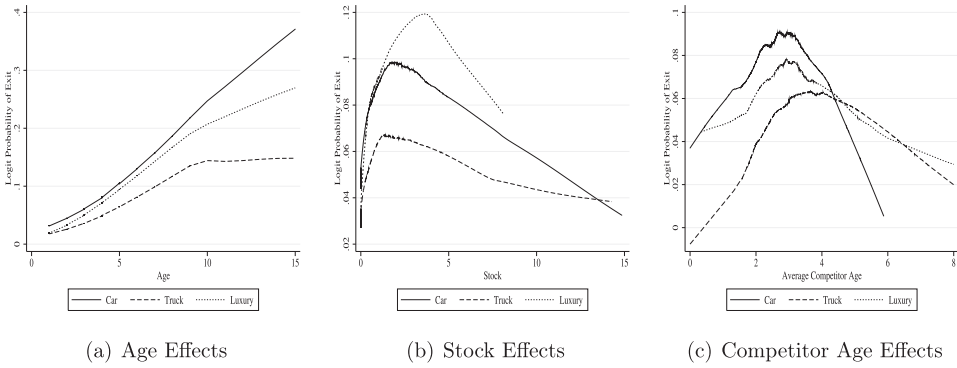(a) Age Effects   (b) Stock Effects   (c) Competitor Age Effects

Fig. 4. Predicted probability of exit. Notes: Each panel displays how the predicted probability of exit changes for different values of the state variables based on coefficient estimates from column 7 of Table 3. Rather than show a scatter plot of predicted probabilities for all observations in our sample we fit a curve through them using a locally-weighted scatterplot-smoothing (lowess) procedure.

4. Estimating the dynamic model

Estimating the dynamic model begins with forward simulations of state variables. Using the preceding optimal policy functions of firms, we forward simulate the market as firms take actions dictated by their policies and transitions of the state variables. Estimation of the second stage then relies on constructing firms' expected present value of future profits. We assume these firm value and profit functions are linearly separable, and take the form,

$$
\begin{aligned}
V_j(\boldsymbol{a}_t(\boldsymbol{\psi_t}, \boldsymbol{\nu_t}), \boldsymbol{\psi_t}, \nu_{jt}; \theta) = {} & W^1(\boldsymbol{a}_t(\boldsymbol{\psi_t}, \boldsymbol{\nu_t}), \boldsymbol{\psi_t}, \nu_{jt}) - W^2(\boldsymbol{a}_t(\boldsymbol{\psi_t}, \boldsymbol{\nu_t}), \boldsymbol{\psi_t}, \nu_{jt}) * \theta_R \\
& + W^3(\boldsymbol{a}_t(\boldsymbol{\psi_t}, \boldsymbol{\nu_t}), \boldsymbol{\psi_t}, \nu_{jt}) * \theta_X + W^4(\boldsymbol{a}_t(\boldsymbol{\psi_t}, \boldsymbol{\nu_t}), \boldsymbol{\psi_t}, \nu_{jt}) * \theta_P.
\end{aligned}
\tag{3}
$$

The present discounted value of static profits given each simulated strategy is W^1. The present value of a firm's redesign costs and scrapping production, are $W^{2*}\theta_R$ and $W^{3*}\theta_X$, respectively. θ_R includes such costs as research and development expenditures for re-design, as well as costs from production line retooling and advertising to inform con-sumers of the new model. Additionally, we allow for firms to receive private values from the actions they take in each time period. Private firm payoffs are given by $W^{4*}\theta_P$. In the following we will assume that the dynamic parameters, θ, are vehicle class specific but common across models within a class.

Explicitly the value function for a model j in vehicle class g is written as,

$$
\begin{aligned}
V_j(\cdot) = {} & \mathbb{E}\left[\sum_{t=1}^{\infty} \beta^{t-1} \pi_{jt}(\boldsymbol{a}_t(\boldsymbol{\psi_t}, \boldsymbol{\nu_t}), \boldsymbol{\psi_t}, \nu_{jt}) \Big| \boldsymbol{\psi_t}\right] - \mathbb{E}\left[\sum_{t=1}^{\infty} \beta^{t} R_{j,t+1}(\boldsymbol{a}_t(\boldsymbol{\psi_t}, \boldsymbol{\nu_t}), \boldsymbol{\psi_t}, \nu_{jt}) \Big| \boldsymbol{\psi_t}\right] * \theta_R^g \\
& + \mathbb{E}\left[\sum_{t=1}^{\infty} \beta^{t} X_{j,t+1}(\boldsymbol{a}_t(\boldsymbol{\psi_t}, \boldsymbol{\nu_t}), \boldsymbol{\psi_t}, \nu_{jt}) \Big| \boldsymbol{\psi_t}\right] * \theta_X^g + \mathbb{E}\left[\sum_{t=1}^{\infty} \beta^{t-1} P_{jt}(\boldsymbol{a}_t(\boldsymbol{\psi_t}, \boldsymbol{\nu_t}), \boldsymbol{\psi_t}, \nu_{jt}) \Big| \boldsymbol{\psi_t}\right] * \theta_P^g.
\end{aligned}
\tag{4}
$$

Before addressing the specifics of simulation and estimation, it is worth dissecting each component of the value function. We calculate the present discounted value of static profits, W^1, in each period given firms' optimal actions chosen in the preceding period. As firm actions update the state variables in the market, we compute $\pi_{jt}(\cdot)$ from the nested logit demand given the states. Summing these static profits while discounting by the fixed rate β, yields W^1. The components W^2 and W^3 are simply counts of the actions taken by the firm over time. For example, the function $R_{j,t+1}(\cdot)$ is an indicator function for whether the firm redesigns in the subsequent period given the current states. Adding up the total number of times the firm redesigns in our simulation and discounting yields W^2. As W^2 enters the value function, it is scaled by θ_R^g, the dynamic cost of redesign.

We also introduce private firm payoff shocks, W^4, as in Sweeting (2013).[24] Private firm payoffs are assumed to be Type 1 extreme value distributed and i.i.d., across firms over time. These shocks are derived from the estimated probability that a firm takes the action we simulate (e.g., the probability of redesign).[25] Applying BBL to estimate our dynamic parameters requires the assumption that firms use stationary Markov perfect pure strategies when they follow the preceding policy functions. As Sweeting (2013) points out, Doraszelski and Satterthwaite (2010) provides a recent proof of the existence of a pure strategy Markov perfect Nash equilibrium (MPNE) in a model with discrete states when the random component of payoffs has unbounded support. Our assumption that firms receive a private value based on the unobservable probability helps facilitate the MPNE assumption.[26]

Outside of the tractability provided, private firm payoffs capture factors that impact the redesign decision of firms which we do not observe in our estimated profit functions. For example, a firm's redesign research and development may spillover to current models through cost savings or increases in consumer demand that are not captured by physical characteristics in our demand estimation. Additionally, these private payoffs will absorb any management changes or new strategic partnerships at the firm level that relate to redesign strategies and firm profitability.

One concern with our equilibrium assumptions may be that redesigns require significant planning and are on relatively inflexible schedules. However, discussion with

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[24] Sweeting (2013) estimates the dynamic cost of repositioning a radio format (see also Jeziorski, 2014). Sweeting (2013) assumes the cost of repositioning is constant across firms within a market (e.g., the cost of switching from Rock to Country in Chicago is identical for all firms and formats). In comparison, we assume the cost of redesign is constant for all models in a vehicle class (e.g., redesign costs are the same for the Honda Civic and Toyota Camry along with all other midsize cars).

[25] Explicitly, $P_{jt}(\cdot) = \varkappa - \log(Prob[a_{jt}(\boldsymbol{\psi_t}, \boldsymbol{\nu_t})])$. Where $\varkappa$ is Euler's constant and a_{jt} is the action (redesign or not) taken by firm j in period t.

[26] We also note that other applications of BBL have addressed Doraszelski and Satterthwaite (2010)'s critiques by assuming dynamic parameters vary within firms over time according to an estimable distribution (c.f., Ryan, 2012 and Kalouptsidi, 2014). Ryan (2012) for instance assumes firms observe a private random investment cost then decide whether to invest in capacity and then by how much. In contrast to Ryan (2012), our actions are strictly discrete – redesign does not vary by degree in our data. We thus follow Sweeting (2013)'s strategy of estimating parameters within a narrow market (vehicle class in our case) that are constant across firms under the assumption that firms use stationary MPNE pure strategies.

members of a development team from one of the domestic "Big Three" suggests that they employ teams of engineers and designers doing overlapping work toward model redesigns, which allows significant flexibility in timing of redesigns. And the data also bear out that there is significant variation in length of redesign, even over time within models. Therefore, we do not constrain the timing of redesigns in our analysis.[27]

Following BBL, the dynamic model is estimated by choosing a vehicle class specific coefficient, $\hat{\theta}^g$, to minimize the objective function for each vehicle class g,

$$Q_g(\theta) \equiv \sum_{j \in \mathfrak{J}_\mathfrak{g}} \left(min\left[0, \widehat{V}_j(\boldsymbol{a}_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t; \theta^g) - \widehat{V}_j(\boldsymbol{a}'_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t; \theta^g)\right] \right)^2. \tag{5}$$

Working from the presumption that each model is choosing the strategy that optimizes its value function, it must be the case in equilibrium that,

$$V_j(\boldsymbol{a}_t(\boldsymbol{\psi}_t, \boldsymbol{\nu}_t), \boldsymbol{\psi}_t, \nu_{jt}; \theta^g) \geq V_j(\boldsymbol{a}'_t(\boldsymbol{\psi}_t, \boldsymbol{\nu}_t), \boldsymbol{\psi}_t, \nu_{jt}; \theta^g). \tag{6}$$

The empirical counterparts of our value function, $\widehat{V}_j$, are calculated by averaging across our simulated shock processes to form expectations. Then, observing actions a_{jt} implies that choosing a'_{jt} would have been suboptimal. We thus minimize the error rate in order to rationalize the firm outcomes we observe.[28]

4.1. Estimation details

Given our estimated policy functions and static-profit results, estimation of the dynamic parameters requires empirical estimates of the value functions under the optimal policy functions and empirical estimates of the value functions under alternative policy functions. In this section, we discuss the specifics of how we construct each of these.

We construct value functions in our sample for each model-year observation by forward-simulating states and actions out 50 periods. In each of these simulations, a model draws marginal cost, redesign and exit shocks. We repeat the simulations for 50 different shock processes. Given the implied transitions of the state variables, we are able to construct redesign and exit decisions for each model for each simulated time period.[29] Specifically, given current states, a firm will redesign next period when its predicted logit inclusive value $\hat{R}_{jt+1} \geq \bar{R}$ and exit when $\hat{X}_{jt+1} \geq \bar{X}$. To best match moments of the data we choose the threshold redesign and exit values $\bar{R} = 0.275$ and $\bar{X} = 0.275$. Table 5 displays the accuracy of our policy functions (percent of correctly predicted outcomes) for various predicted-value thresholds, which informs our choice of 0.275. At a standard

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[27] In practice, and in our simulations, no model ever actually redesigns in consecutive years.
[28] Miller and Laurence (1974) finds that in the case of a monopolist, if consumers are forward-looking there is no profit gain from planned obsolescence. This is supported by the empirical results in Chevalier and Goolsbee (2009). In contrast, Waldman (1993) finds that firms do have an incentive to strategic obsolete their production. If we are in the world of Miller and Laurence (1974) and Chevalier and Goolsbee (2009) the empirical moments related to perturbations of the policy function with respect to the obsolescence motive effects will be weak. Weak instruments can cause the objective function to have flat

Table 5
Performance of policy functions.

	Sample	Logit policy threshold ($\bar{R}$ or $\bar{X}$)						
		0.10	0.20	0.25	0.275	0.30	0.40	0.50
% Correct if								
Redesign = 1	100%	82.4%	55.2%	43.7%	37.0%	32.3%	16.9%	6.9%
Redesign = 0	100%	69.4%	86.1%	91.1%	92.9%	94.3%	97.7%	98.6%
Exit = 1	100%	14.8%	12.7%	12.4%	12.4%	12.2%	10.8%	9.3%
Exit = 0	100%	99.1%	99.3%	99.3%	99.3%	99.3%	99.4%	99.4%
Fraction of sample								
Redesigned	9.8%	35.6%	18.0%	12.3%	10.0%	8.3%	3.8%	2.0%
Exited	6.9%	1.8%	1.5%	1.5%	1.4%	1.4%	1.2%	1.1%

Notes: This table presents the fraction of models redesigning and exiting as predicted by our estimated policy functions when setting various thresholds for the logit inclusive values alongside and compares the predicted action to the actual action in the data.

threshold of 0.5, non-events are very precisely matched, but events (redesign or exit) are rarely matched correctly. In other words, events are underpredicted for the sake of model fit. At lower levels (such as 0.10), events are more often matched correctly, but then we get over-prediction of the events at the expense of correctly predicting the non-events. We have found that the moments of the simulations best fit the actual data at our preferred thresholds.

These redesign and exit decisions, coupled with our estimated utility functions and the ownership structure of each model, allow us to calculate the static profits of each model in each simulated time period. We use these simulated states to construct $\widehat{W}^1(\boldsymbol{a}_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t)$ the empirical analog of $W^1(\boldsymbol{a}_t(\boldsymbol{\psi}_t, \boldsymbol{\nu}_t), \boldsymbol{\psi}_t, \nu_{jt})$ in Eq. (4). Our simulations also produce estimates of each component of the value function, as $\widehat{W}^2(\boldsymbol{a}_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t)$ and $\widehat{W}^3(\boldsymbol{a}_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t)$ are the summations of the redesign and exit actions taken, and $\widehat{W}^4(\boldsymbol{a}_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t)$ is based on the estimated probability of the firm's chosen action.[30] Lastly, the second stage is used to estimate the dynamic parameters of Eq. (4) (θ_R^g, θ_X^g and θ_P^g) for each vehicle class, in a way that "rationalizes" the estimated value functions. The intuition of the estimator is based on the presumption that our optimal policy functions should lead to greater profits than any alternative policy function.

Applying the second-stage estimator, therefore, requires constructing value functions for alternative policies and the transitional dynamics that these alternatives imply. BBL demonstrates that by perturbing the estimated policy functions, the second stage estimator is consistent. Srisuma (2010) points out linear perturbations can lead to inconsistencies and proposes perturbations of the form, $a'(\cdot) = \epsilon * a(\cdot\,; \theta_0)$ to be more stable.

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regions, thereby affecting identification (see, Knittel and Konstantinos, 2014 for a discussion of this). In practice, we do not find evidence of flat regions of the objective function, consistent with Waldman (1993).

[29] Note that most of our state variables are constructed from market realizations (e.g., average age of competitors).

[30] To reiterate, $\widehat{W}^4(\boldsymbol{a}_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t) = \sum_t \beta^{t-1} P_{jt}(\cdot)$ where $P_{jt}(\cdot) = \varkappa - \log(Prob[a_{jt}(\boldsymbol{\psi}_t, \boldsymbol{\nu}_t)])$. With $\varkappa$ denoting Euler's constant and a_{jt} is the action (redesign or not) taken by firm j in period t.

Table 6
Estimates of dynamic parameters.

Type	Class	Redesign cost ($M)	Scrap value ($M)	Private value ($M)
Car	COMPACT	1119.950	4259.150	99.480
		(1094.2,1142.9)	(3921.4,4583.7)	(72.1,126.9)
	FULL	1283.976	5576.464	299.600
		(1257.9,1313.6)	(5209.9,5938.4)	(268.5,332.2)
	MID	1657.509	8305.982	499.094
		(1601.3,1710.5)	(7703.3,8912.2)	(451.6,549.9)
Truck	PU	3049.221	8169.166	496.914
		(2922.5,3193.2)	(6324.4,10023.4)	(346.5,651.8)
	SUV	1320.915	5325.169	381.302
		(1296.9,1344.8)	(5053.3,5621.4)	(356.9,408.5)
	VAN	1712.673	3784.817	159.762
		(1676.7,1749.6)	(3215.3,4350.7)	(120.4,201.6)
Luxury	LUX	860.344	5852.855	431.069
		(835.8,881.1)	(5590.4,6086.9)	(406.3,451.8)
	SPORT	1986.206	20267.543	1690.631
		(1906.9,2059.6)	(19236.0,21471.1)	(1603.4,1789.9)

Notes: Each class is bootstrapped 500 times, 99% confidence intervals for each parameter are in parentheses.

We thus draw $\epsilon \sim Uniform[0, 2]$ independently for the exit and redesign policies for 500 perturbed policies applied to each simulation.[31] Plainly, we randomly scale up or down the probability firms take particular actions. Using these perturbed policy functions we forward simulate each model's value function in parallel to the optimal path. This allows us to construct a set of alternative value functions that are also linear functions in θ. These simulations under alternative policy functions enable us to construct Eq. (5). We then choose the θs to minimize this sum of squares. Appendix A further details the non-linear search methods used for estimation, but we opt for a simple Newton–Rhapson search as it is shown to lead to consistent estimates regardless of starting value choice.

4.2. Dynamic parameter estimates

Table 6 presents our estimates of the dynamic parameters using the BBL technique. Our estimates suggest that redesign costs average nearly $1.6 billion across all types of vehicles, and bootstrapped errors indicate that these estimates are fairly precise, with all of them different from zero at the 1% significance level. There is noticable heterogeneity across types of vehicles. Redesign costs are smallest for luxury vehicles at around $900 million. For cars, vans and SUVs we estimate redesign costs between $1.1 and $1.7 billion. Our largest estimates are for pick-ups at over $3 billion. While automobile firms undoubt-

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[31] That is, each information shock is perturbed 500 times. We have also investigated various forms of perturbations, including the additive perturbations suggested by BBL, and the resulting estimates are similar across either method.

edly know (at least, *ex post*) their redesign costs, these numbers are closely guarded and we cannot verify the credibility of these estimates with publicly available information. However, we compare our estimates to a variety of sources in the popular press. A recent *AOL Autos* article states that the price tag of a remodel starts at $1 billion and, "It can be as much as $6 billion if it's an all-new car on all-new platform with an all-new engine and an all-new transmission and nothing carrying over from the old model." A recent *Forbes* article suggests the developments costs are at least $1 billion. In addition, a *Business Insider* article quotes Nissan as saying that they normally spend $300–500 million on a remodel. Finally, a private conversation with a former manager in one of the major U.S. automobile manufacturers suggests that our estimates are very reasonable.

Unlike redesign costs, scrap values are likely something that is even less observable, as they represent an opportunity cost to the continuation of production of the model. Our scrap values are estimated to be significantly larger in general than redesign costs. While this seems quite plausible to us, it is difficult to compare these estimates to anecdotal evidence on these values, and we note that there are relatively few exits of models in our sample (and simulations) from which to identify these estimates in our data and account for in simulations. This contrasts with the high frequency of redesigns, the focus of our study.

There are additional issues surrounding firm exit in this model. Because the methodology does not lend itself to modeling entry directly, as that would require endogenously choosing attributes and unobserved quality, allowing for exit in our model implies that in the limit no vehicles will exist. While this does not happen in our simulations – only around 15% of models exiting at the conclusion of our simulations – there is still a possibility that weak identification of scrap values are influencing our redesign estimates, which are the purpose of the paper. We investigate how shutting down exit affects our results. Table B.1 in Appendix B presents estimates of the dynamic model assuming firms do not have the option to scrap their models. The relative rankings of redesign costs stay the same, though the levels fall substantially. If one does not allow exit in the model, then firms redesign more in our simulations and this increased frequency of redesigns leads to an underestimate of the cost of redesign. This shows the importance of modeling exit decisions in our framework.

5. Welfare estimates

Given our estimates of redesign and scrap values, we now have a fully dynamic model from which we can construct and track estimated welfare and firm value over time. In particular, our measure of welfare within vehicle class each period is the present discounted value of the nested-logit inclusive value (see Nevo, 2003),

$$U_{gt} = \mathbb{E}\left[\sum_{t=1}^{\infty} \beta^{t-1} * \frac{1}{\alpha} ln\left(\sum_{g}\left(\sum_{j\in\mathfrak{J}_g} e^{\frac{\delta_{jt}}{1-\sigma}}\right)^{1-\sigma}\right) * Ms_{gt}\right]$$
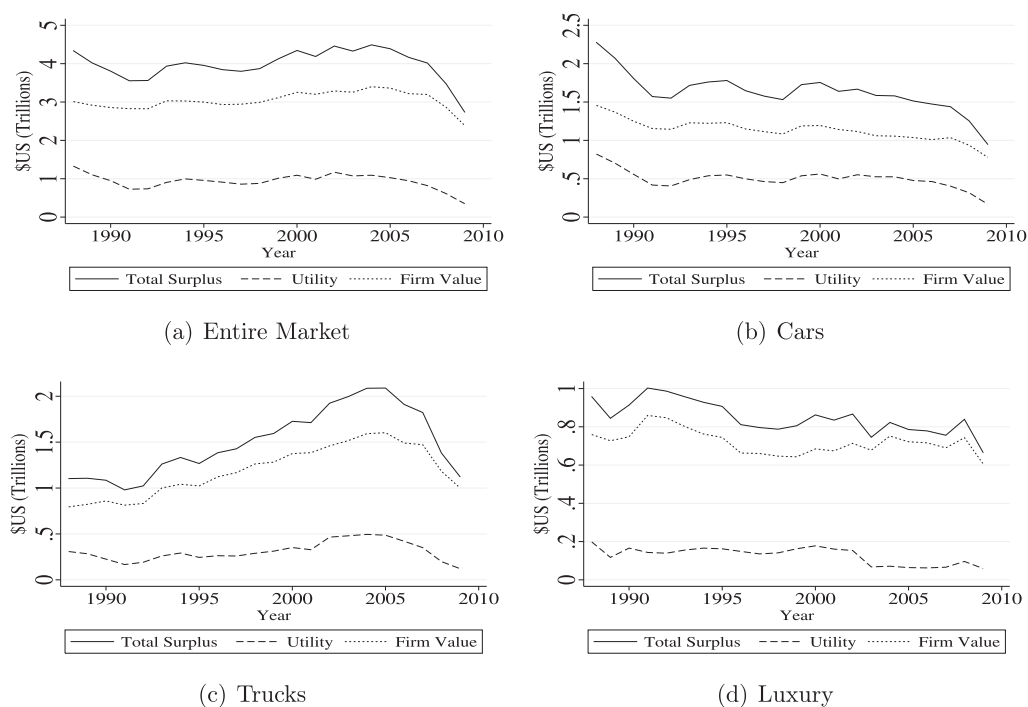
(a) Entire Market

(b) Cars

(c) Trucks

(d) Luxury

Fig. 5. Welfare estimates.

such that the total utility from new auto purchases in period t is $\Sigma_g U_{gt}$.[32] We then apply the within class estimates of redesign cost and scrap value to each of our 50 forward simulations and discount by the factor $\beta = 0.95$ to calculate present discounted profits (or "Firm Value") and present discounted utility in dollars (or "Utility") for each model in our sample and then sum up across models within each vehicle group. Fig. 5 provides baseline estimates of welfare in the model over time. Panel (a) of Fig. 5 graphs discounted present value of firm value, consumer utility, and total welfare for the automobile market over a 50-year horizon at every year of our sample.

Fig. 5 displays a number of important features of the U.S. automobile market. First, as shown in Panel (a), firm value in the entire market is around $4 trillion for most years in our sample, which means an average of about $80 billion in annual firm value flow.[33] Panels (b), (c), and (d) of Fig. 5 break out the automobile market into three major segments. These are "cars," which include standard compact, midsize, and full-size vehicles; "trucks," which includes minivans, pickups, SUVs, and vans; and "luxury"

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[32] We take the increase in utility as real in the sense that, absent the redesign, consumers' utility would suffer. One could imagine, for example, an argument that redesigns only change welfare because they update what is "in style," whereas if the redesign had not taken place, their older version is still viewed as "in style." We abstract from this possibility.

[33] These estimates seem plausible given stock market valuations of the auto industry. For instance, the market capitalization of auto manufacturers is around $8.5 trillion as of January 2013.
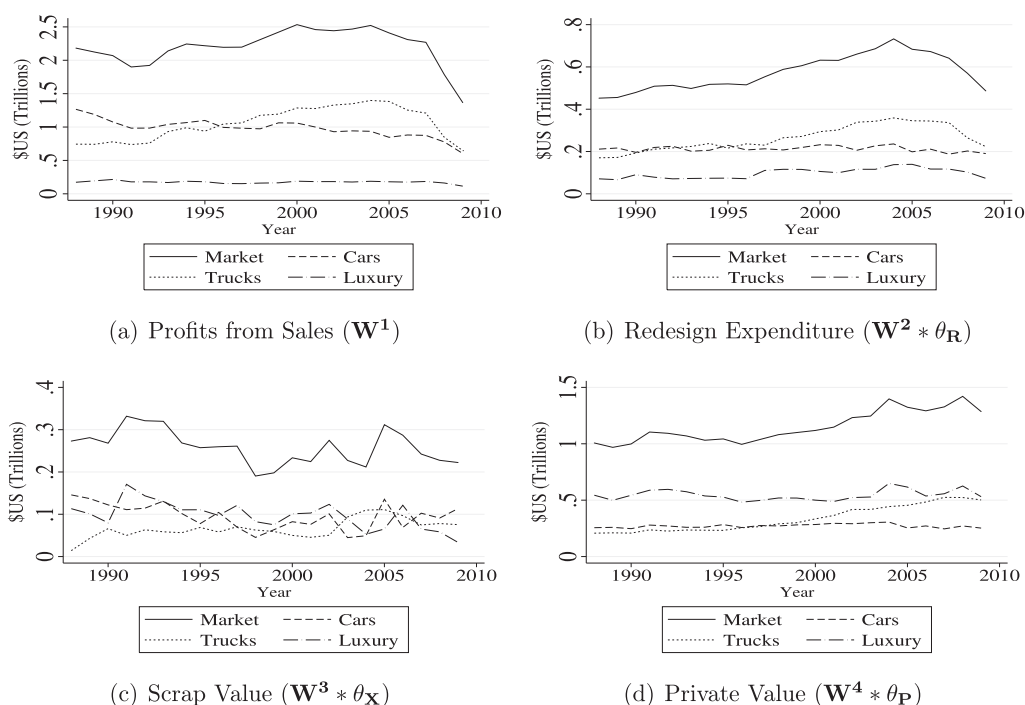
(a) Profits from Sales ($\mathbf{W^1}$)

(b) Redesign Expenditure ($\mathbf{W^2} * \theta_{\mathbf{R}}$)

(c) Scrap Value ($\mathbf{W^3} * \theta_{\mathbf{X}}$)

(d) Private Value ($\mathbf{W^4} * \theta_{\mathbf{P}}$)

Fig. 6. Decomposing firm value estimates.

vehicles. There are a number of interesting observations that one can take from Fig. 5. First, firm value is high relative to consumer surplus (about a ratio of 2 to 1), suggesting that firms are extracting a significant amount of the total surplus in the automobile market.[34] Second, the recessions of the early 1990s and late 2000s show up quite clearly in our estimates, with firm values and total welfare falling considerably. Third, the truck and luxury segments of the market appear to have been more affected by the recent recession than the standard cars market.

Fig. 6 further decomposes the firm value component of welfare by the three main automobile segments and the three components of firm value—profits from sales, redesign expenditures, and scrap value. As one can see in Panel (a), the truck segment (which includes minivans and SUVs) increased substantially from the early 1990s until the recent recession in terms of its contribution to firm profits. The segment even surpassed the standard car segment in the late 1990s, but also suffered the largest decline when the recent recession hit. Redesign expenditures by vehicle segment show a relatively consistent ranking over time, with the truck segment accounting for about half of automobile manufacturers' redesign expenditures, with cars next, and the luxury segment (a relatively small market segment) accounting for the least amount of redesign expenditures. The

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[34] We note that our estimates are for the primary automobile market, as we do not model the secondary car market. We will discuss this more below.

estimated scrap value component is very small compared to the other two components and fairly volatile. All segments are estimated to have similar total scrap values, with considerable variation over time.[35]

6. Using the dynamic model to examine the effect of competitive redesign and obsolescence motives on welfare

We now use our model to address our initial goals in the paper—analyzing the relative role of competitive redesign and obsolescence motives in affecting redesign decisions and ultimately firm profits and overall welfare. This allows us to understand how much these competitive redesign and obsolescence considerations affect how efficiently the market operates. Our numerical exercise is to suppose a social planner can increase or decrease the probability of redesign in the market. That is to say, given our estimated costs of redesign and market demand parameters, the planner will strengthen or weaken the obsolescence and competition motives driving redesign for certain models in the market. To be clear, we are not performing counterfactual analyses as we do not solve for a new Markov perfect equilibrium as the planner adjusts the motives for redesign. In simple terms, we are providing numerical comparative statics for the redesign and welfare effects from changing firm responses to the competitive and obsolescence motives driving redesign given the dynamic parameters we have estimated.

To do this we undertake a set of simulations with our estimated dynamic model where we intensify and reduce the impact of both the competition and obsolescence motives and observe the impact on welfare. Fig. 7 provides a contour map of the patterns of redesign activity when the planner alters the strength of the forces driving redesign. The horizontal axis indicates the strength of the obsolescence response, while the vertical axis indicates the strength of the competitive redesign response. Point (1,1) is the baseline responsiveness of firms to the obsolescence and competitive redesign motives associated with our estimated coefficients. Moving away from this baseline point changes the responsiveness of firms to these motives relative to the baseline. For example, moving to a value of 1.5 on either axis indicates that the responsiveness of that motive (obsolescence or competitive redesign) is 50% higher than in our baseline.

Fig. 7(a) begins by calculating the probability that the average model undergoes a redesign in each of these experiments. This ex ante average model last had a redesign four years ago, faces competitors that last redesigned their model three years ago on average, and has seen six competitors redesign their model since its last redesign. The average model also has a stock of sales around 2 million units. Given these characteristics, our policy function estimates this model has a 7% logit inclusive value of redesigning next period. We can see that as the planner strengthens the responsiveness to obsolescence and competitive redesign (moving northeast on the diagram), the probability of redesign

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[35] Our results are robust to a number of alternative model assumptions, including whether we model firms as single product or multi-product firms and whether we model and allow for exit. Appendix B provides more details.
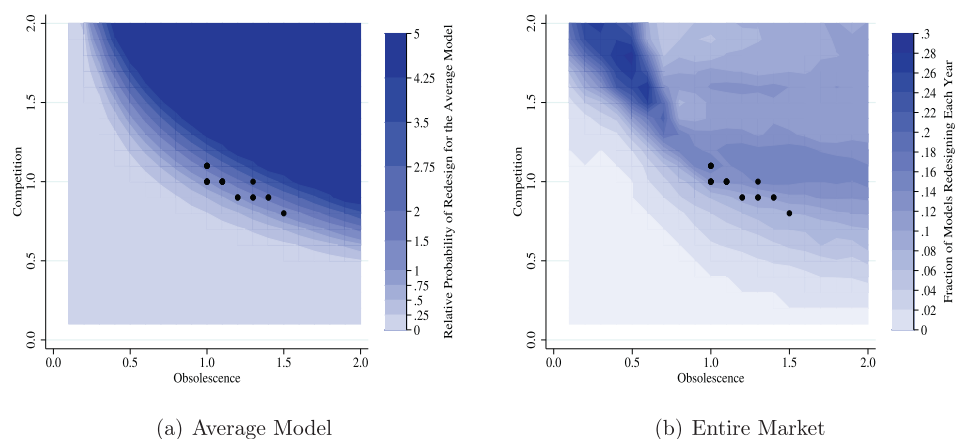
(a) Average Model   (b) Entire Market

Fig. 7. Contour map of differences in redesign activity for different relative strengths of the competitive redesign and obsolescence motives. Notes: Panels (a) and (b) provide a contour map of the changes to the average probability of redesign of a model and the average annual fraction of all models redesigning, respectively, when one increases or decreases the obsolescence and/or competitive redesign responses by firms. The horizontal axis indicates the strength of the obsolescence response, while the vertical axis indicates the strength of the competitive redesign response. Point (1,1) is the baseline responsiveness to the obsolescence and competitive redesign motives associated with our estimated coefficients. Moving away from this baseline point changes the responsiveness these motives relative to the baseline. For example, moving to a value of 1.5 on either axis indicates that the responsiveness of that motive (obsolescence or competitive redesign) is 50% higher than in our baseline. Darker shades indicate higher values of the average probability of redesign or average annual fraction of all models redesigning, and ● denotes the combination of relative competitive redesign and obsolescence strengths that achieve maximum welfare.

increases rapidly on average – magnifying the obsolescence and competitive redesign motive effects both by 1.3 or more makes the average model 5 times more likely to redesign next period. For exposition, we truncate Fig. 7(a) at 5 times more likely, because this level implies the average model will redesign next period with certainty. Conversely, as the planner moves southwest on the diagram the probability of redesign falls.

Fig. 7(b) extends this analysis to the entire market. Here we plot the fraction of models in the data that are predicted to redesign next period. At our baseline point (1,1), around 12% of the entire market redesigns (looking across all market segments). We see that the highest rates of redesign are around 30% of the market, and occur where the obsolescence motives are slightly weakened and the competitive motives are strengthened (i.e., the northwest corner). Additionally, we plot the planner's choices that maximize total welfare in the market (denoted by ●). The following discusses the consequences of the planner strengthening and weakening the motives for redesign, but we can see total welfare responds favorably to increases in obsolescence and slight decreases in competitive redesign motives that result in only modest increases in the overall rate of redesign in this market.

To identify welfare under different social planner policies, we perform a grid search varying the strengthening and weakening of the motives of redesign (obsolescence and competitive redesign) from 0 to 2 in 0.1 increments. We search for the pair that maximizes
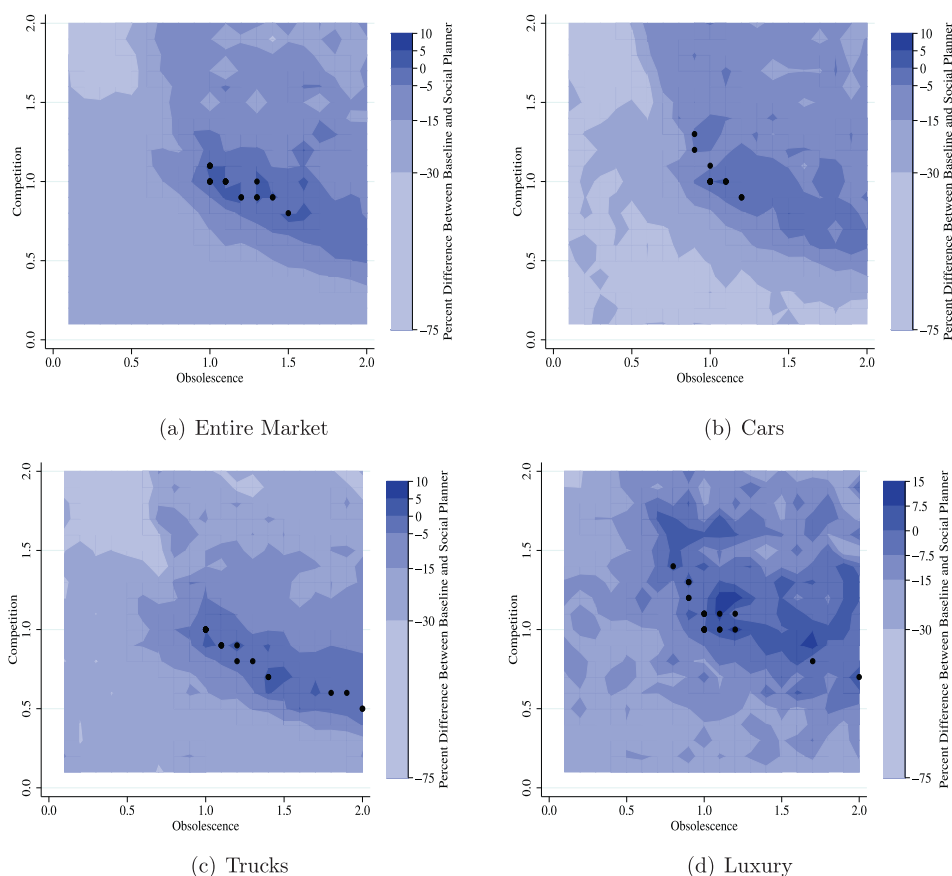
(a) Entire Market

(b) Cars

(c) Trucks

(d) Luxury

Fig. 8. Contour map of welfare differences for different relative strengths of the competitive redesign and obsolescence motives. Notes: Each panel provides a contour map of the changes to welfare when one increases or decreases the obsolescence and/or competitive redesign responses by firms. The horizontal axis indicates the strength of the obsolescence response, while the vertical axis indicates the strength of the competitive redesign response. Point (1,1) is the baseline responsiveness to the obsolescence and competitive redesign motives associated with our estimated coefficients. Moving away from this baseline point changes the responsiveness of these motives relative to the baseline. For example, moving to a value of 1.5 on either axis indicates that the responsiveness of that motive (obsolescence or competitive redesign) is 50% higher than in our baseline. Darker shades indicate higher values of welfare in percentage terms relative to the baseline, and ● denotes the combination of relative competitive redesign and obsolescence strengths that achieve maximum welfare.

total welfare in each year of our sample, forward simulating out 50 years from that given year. Therefore, we can have a different pair of motives in each year.

A convenient way to summarize our results is through the use of a contour plot that displays the percentage difference of the sum of total welfare between the base point and alternative coordinates across each year in our sample. Fig. 8 plots these for the market as a whole, as well as for each of the car, truck, and luxury vehicle segments of the market. The baseline scenario welfare is at the center of these plots, where both parameters are equal to unity. Darker shades in the plot represent higher welfare levels

and the black circles represent combinations of planner choices that maximize welfare in at least one period, which we term our "optimal simulation."

Welfare is relatively high in the baseline scenario, and it is clear that when the planner reduces the responsiveness of the redesign policy function to either (or both) of the competitive redesign or obsolescence motive effects results in major welfare losses as redesign slows drastically. The worst results come from fully strengthening the competitive redesign motive and fully weakening the obsolescence motive. Increasing responsiveness of redesign to each motive results in much smaller welfare losses. In other words, too frequent redesigns in this market would be much less costly than too infrequent redesign activity.

While our welfare is relatively high in the baseline scenario, our contour of simulations suggests that welfare could be improved in this marketplace by moving southeast from the baseline to a region that represents a reduced competitive redesign motive effect and a greater obsolescence motive effect. Referencing the black circles in our plot, which represent the highest welfare levels obtained in our simulations, they suggest that in the typical year, welfare is maximized by reducing the competitive redesign motive by roughly 20%, but increasing the obsolescence motive by between 20% and 50%. The welfare increase between the optimal simulation and our baseline is between 1.5% and 15%. Interestingly, these observations are true not only for the entire market, but also for each market segment. All four plots suggest that the welfare-maximizing policy functions correspond to a ridge in the welfare mapping that runs from the northwest to the southeast in Fig. 8.

We can also use our simulations to show how consumer utility, firm value, and total welfare in these optimal simulations compare to the baseline estimates in each year. It is possible that either firms or consumers can be made worse off in the optimal simulation, even if total welfare is a bit higher. And these comparisons may vary year to year in the market. Fig. 9 plots the welfare difference of the optimal simulation to the baseline for consumer utility, firm value, and total welfare over the years of our sample. We plot these for the entire market in Panel (a), as well as for each of the car, truck, and luxury vehicle segments of the market in Panels (b)–(d). Under the optimal simulation, firm value is generally higher than the baseline. In contrast, consumer utility under the optimal simulation can sometimes be lower than for our baseline scenario. Lower relative consumer utility in the optimal simulation is especially pronounced from 2004 and 2005 and from 2008 and 2009. These periods notably encompassed both an increase in gasoline prices and the beginning of the Great Recession. Comparing the results across market segments, we find that the luxury vehicle segment has the largest welfare gain (positive percentage) in the simulation relative to the baseline, while the car market segment has the smallest, and the optimal outcome is most often the baseline.

Finally, in Fig. 10 we show the relative differences between the optimal simulation and the baseline for the components of firm value (profit from sales, redesign expenditures, and scrap values). As with Fig. 9, we show these for the market as a whole, as well as for each of the car, truck, and luxury vehicle segments of the market, in four separate
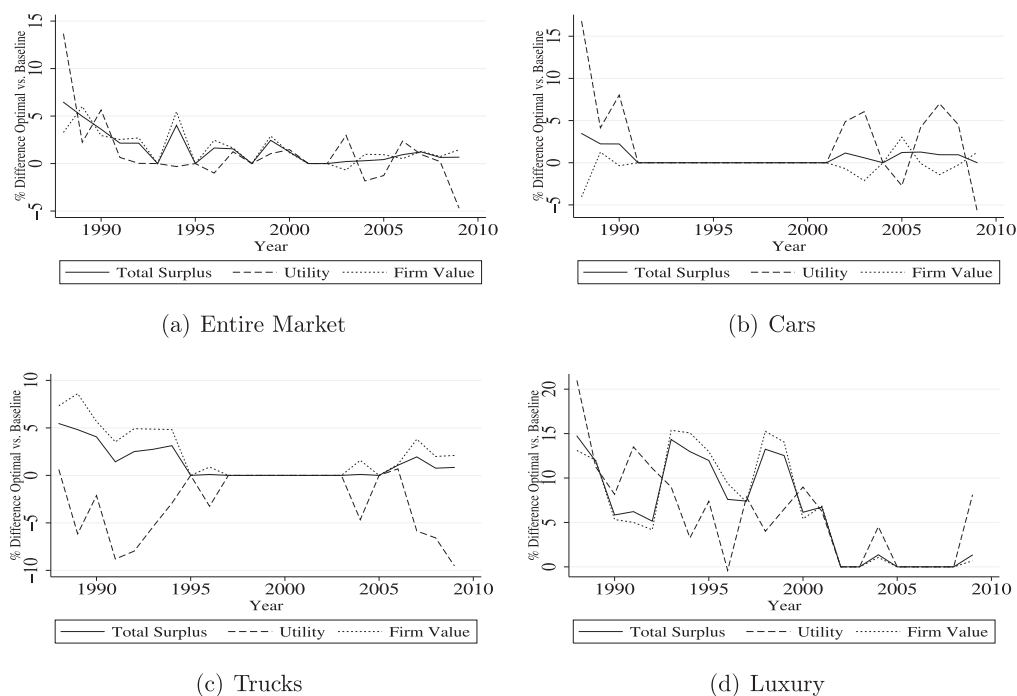
(a) Entire Market

(b) Cars

(c) Trucks

(d) Luxury

Fig. 9. Welfare components: welfare differences between the social planner relative to baseline policy functions .

panels. As shown above, the optimal simulation is generally one where the competitive redesign motive is weakened and the obsolescence motive is strengthened. These should have opposite effects on how often firms redesign and, thus, total redesign expenditures. As seen in Fig. 10, these motives vary significantly across vehicle class. The weaker competitive redesign motive in the optimal simulation appears to dominate for trucks with respect to the effect on redesign expenditures, as expenditure is lower in the optimal simulation relative to the baseline by 20%, or $40 billion (about $0.8 billion per year), on average. For cars, we see the opposite. In the optimal simulations, redesign expenditure increases on average by 30%, or $60 billion (about $1.2 billion per year). For the entire market, which includes luxury vehicles, total expenditure rises and falls from 40% to −10% depending on the period.

We interpret the change in firm behavior from the optimal social planner choice as enhancing social efficiency by reducing inefficient redesigns coming from competitive redesign, enhancing redesigns valued by consumers that come from obsolescence, and discontinuing weak varieties. Figs. 9 and 10 demonstrate that the more efficient timing of redesigns results in relatively little change to profits from sales and consumer welfare. Welfare gains could thus be realized as firms acquire significant savings by eliminating excess redesigns with minor distortions to the final goods market.
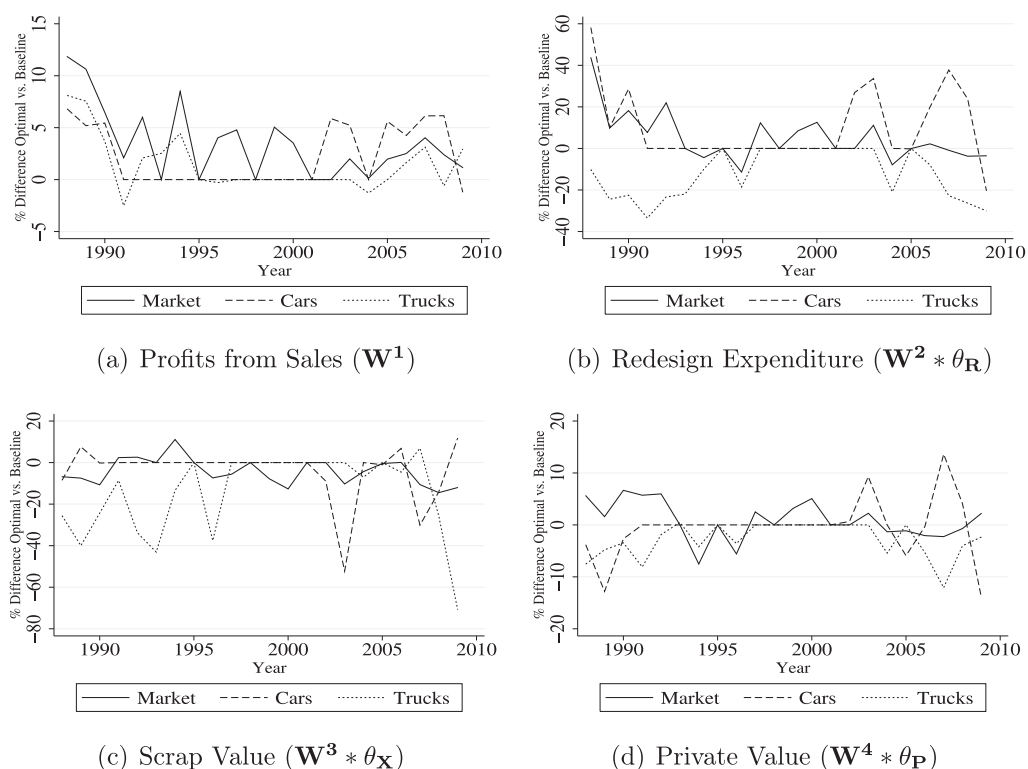
(a) Profits from Sales ($\mathbf{W^1}$)

(b) Redesign Expenditure ($\mathbf{W^2} * \theta_\mathbf{R}$)

(c) Scrap Value ($\mathbf{W^3} * \theta_\mathbf{X}$)

(d) Private Value ($\mathbf{W^4} * \theta_\mathbf{P}$)

Fig. 10. Decomposing firm value components: welfare differences between optimized policy functions relative to baseline policy functions.

7. Secondhand market considerations

Our model and welfare analysis is clearly focused on the new automobile market. We account for the secondhand market for automobiles in two indirect, but important, ways in our model. First, it is implicitly accounted for as part of the outside option consumers have in the discrete-choice demand model we specify. Second, the appeal of secondhand automobile models is presumably a factor in how quickly demand for new automobiles falls as the current model ages.

One may be concerned that the channels which produce welfare gains in our characterization of the optimal simulation may be at the expense of used car value. Explicitly modeling the secondhand market is beyond the scope of this paper, and therefore we cannot describe how redesigns of new automobiles directly affect transactions and welfare of participants in the secondhand market. However, to get some sense of the possible welfare effects on the secondhand automobile market, we do the following. First, using auction data of secondhand vehicles, we estimate the impact of redesigns of a model on the current generation of used automobiles of the same model, controlling for other observable factors, such as annual depreciation (which average around 20%) and man-

ufacturer and automobile class effects. From this analysis, we estimate that a redesign leads to, at most, a 4% fall in the value of the used car models of the most recent model generation. Furthermore, this result is not statistically robust. We also assume that the value of used automobiles from models more than one generation ago see their value fall to zero. This is likely a very strong assumption, but will give us an upper-bound estimate of how much impact redesigns have on the secondhand market.[36]

Using these assumptions, we can estimate the impact of redesigns on the total value of the stock of used automobiles in our simulation of the model. In our baseline simulations, we find that if we eliminate redesign activity there is an increase of about $250 billion (or roughly 7.5%) in the total value of used vehicles. Applying the same thought experiment to our optimal simulation, eliminating redesign activity implies an increase of about $200 billion (or roughly 7%) in the total value of used vehicles. To reiterate, we think of these effects as upper bounds on the losses from redesign activity. And these estimated losses in the secondhand market are small compared to the welfare losses from eliminating redesign in the new automobile market, where eliminating redesign in the baseline scenario leads to anywhere from a 60% to 75% loss in total surplus (or approximately $2 trillion).

8. Conclusion

This paper builds the first empirical structural model of product redesign in the auto industry. We use it to examine redesign decisions in the U.S. automobile market and their effects on firm profits, consumer utility, and total welfare. Unlike the few prior empirical studies of product redesigns, we find that both redesign competition among models and planned obsolescence to recapture market share play important roles. Simulations using our estimated dynamic model find evidence of wasteful redesign competition that then precludes more redesign activity targeted to obsolete models at the optimal time. We find that welfare would be maximized by reducing the competitive redesign channel by roughly 20%, but increasing the obsolescence channel by between 20% and 50%. This would have only a modest net effect on redesign expenditures and still yield welfare increases of roughly 3%.

A handful of existing studies have estimated consumer gains from new automobile product varieties. In particular, Blonigen and Soderbery (2010) estimate consumer valuation of new product variety to be on the order of 10% of utility. As noted in the introduction, the redesign of existing autos occurs twice as often as the introduction of new varieties. Our analysis points to the importance of redesigns, as the redesign activity in our simulations has nearly six times the effect on consumer welfare as previous estimates of new variety introduction.

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[36] However, we note that since redesigns happen about every 5 years and annual depreciation is around 20% annually, the residual value of these used automobiles beyond the most recent generation will be quite small anyway.
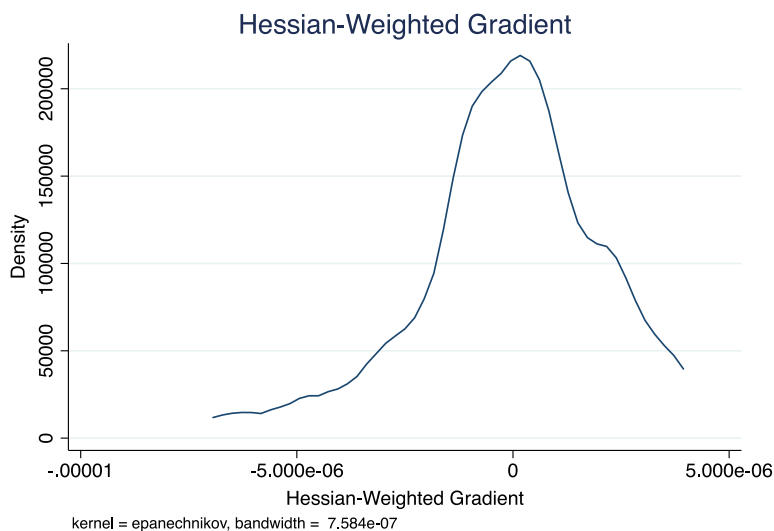
Hessian-Weighted Gradient

kernel = epanechnikov, bandwidth = 7.584e-07

Fig. A.1. Hessian-weighted gradient of converged sets of parameters.

Appendix A. Details of the non-linear search

Our empirical model requires a non-linear search over the dynamic parameters representing the cost of redesign and the scrap value of eliminating a model. We investigated the sensitivity of this non-linear search to both starting values and non-linear search algorithms drawing on the lessons learned in Knittel and Konstantinos (2014). Ultimately, we found that unless one uses the Nelder–Mead (Simplex) algorithm, convergence is always met in the same location (down to at least the fourth decimal point) of the parameter space. Furthermore, if we restart the non-linear search at points where the Nelder–Mead algorithm "converged" and use another non-linear search algorithm, we again end up where the non-Nelder–Mead algorithms converge, which corresponds to a smaller GMM objective function value. That is, the Nelder–Mead algorithm appears to converge at points that are not actually extrema.

We used the *Optimize()* command within Stata to estimate the GMM problem associated with the dynamic parameters.[37] While Stata is more limited than alternative programs, such as Matlab, in terms of the options for undertaking the non-linear search,

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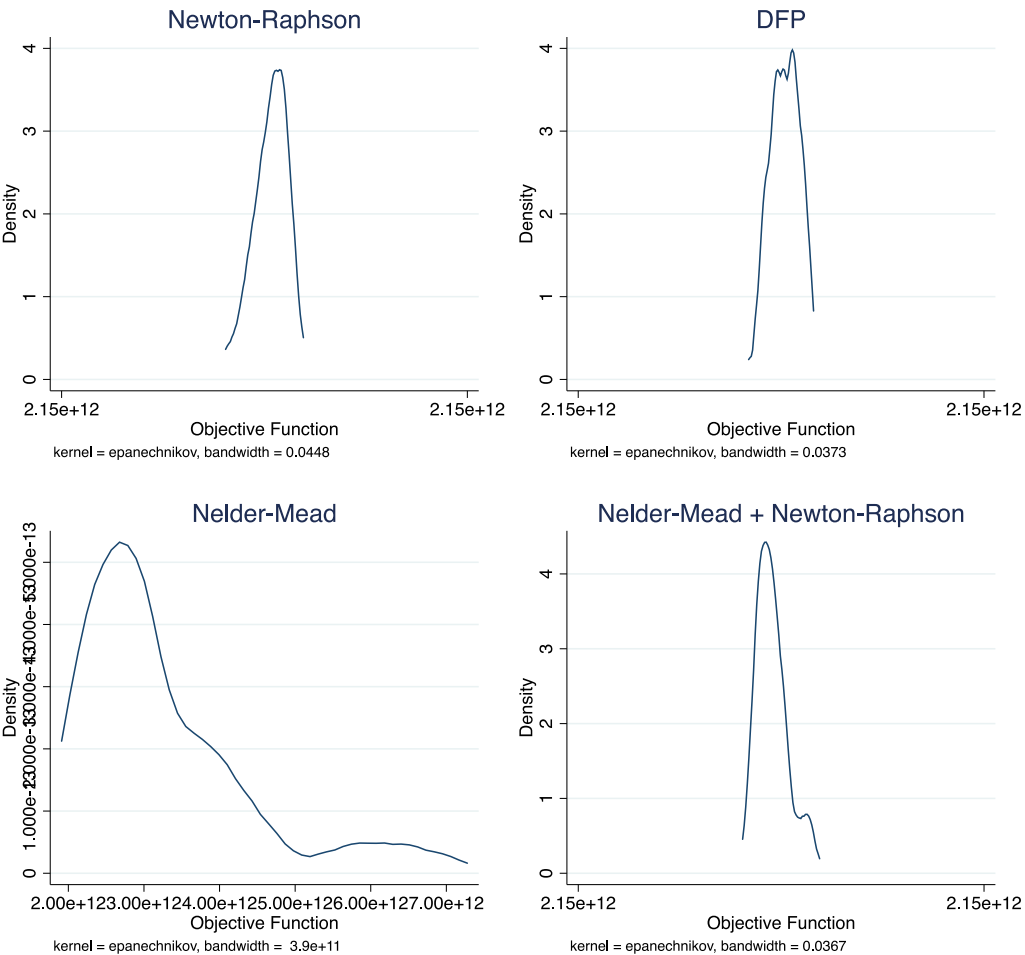[37] See *man Optimize* within Stata for more information.

Fig. A.2. Objective function across all converged sets of parameters.

it includes a Simplex algorithm, a Newton–Raphson algorithm, and three quasi-Newton algorithms. Stata also allows the programmer to set starting values and tolerances.

Convergence is dictated by three tolerances: *ptol*, *vtol*, and *nrtol*. Convergence is reported if one of three things happens. (1) If the largest relative change in parameters (i.e., $(\beta^h - \beta^{h-1})/\beta^h$ for iteration h) is smaller than *ptol*; (2) If the change in the objective function value between two iterations is smaller than *vtol*; (3) If the scaled gradient vector (i.e., $gH^{-1}g'$, where H is the Hessian) is smaller than *nrtol*. We use Stata's default tolerances for *ptol* (1e−6), *vtol* (1e−7), *nrtol* (1e−5), but have found that tightening these tolerances does not appreciably change our estimates.

For our initial investigation of whether starting values and/or the non-linear search algorithm yield different results, we used three of Stata's non-linear search algorithms and a fourth which is a hybrid of two. Specifically, we use the Nelder–Mead (Simplex)
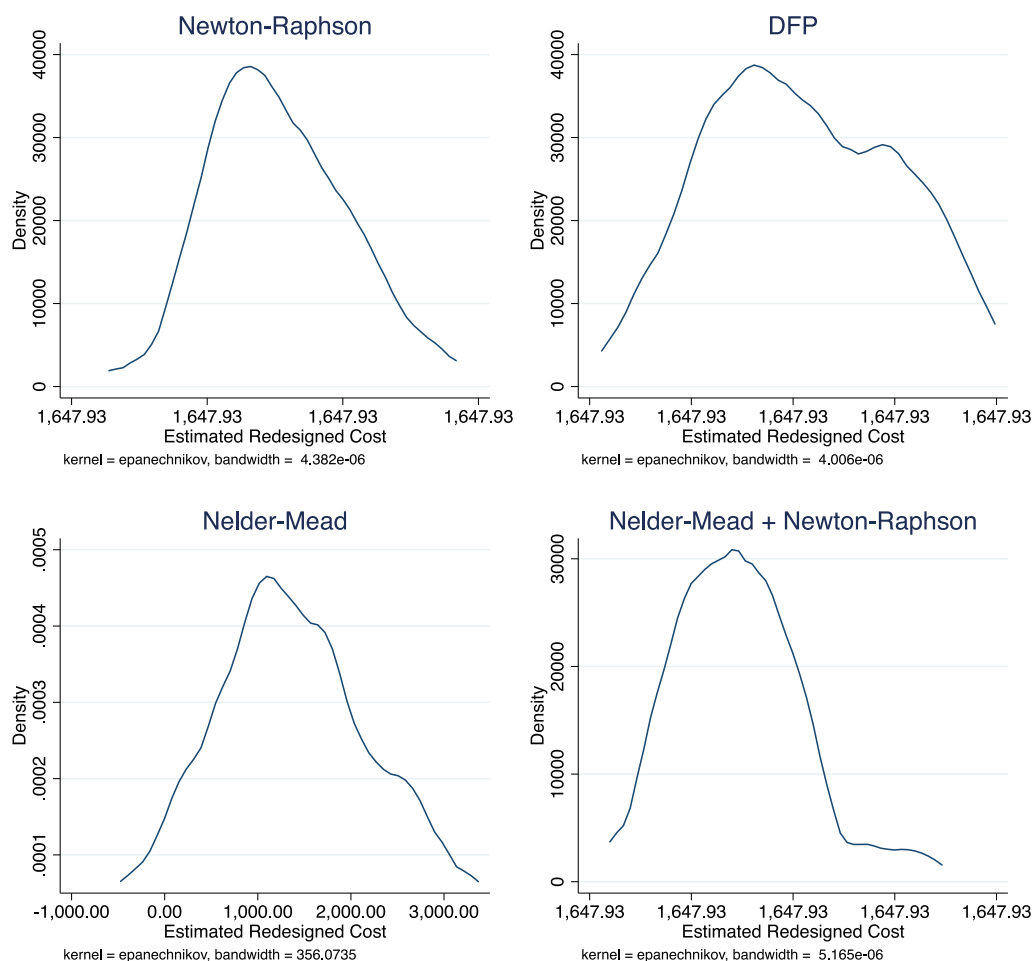
Fig. A.3. Estimated redesign cost across starting values and algorithms.

algorithm, the Newton–Raphson, and the Davidson–Fletcher–Powell (Quasi-Newton) algorithms. Our hybrid approach uses the Nelder–Mead algorithm until convergence is met, and then shifts to the Newton–Raphson algorithm. For each of these four algorithms, and each of the three dynamic parameters, we used nine different starting values (representing millions of dollars): −900, 100, 1100, 2100. The intersection of these three sets yields 64 starting-value combinations for each algorithm.

Fig. A.3 and A.4 summarize our results from this exercise, when we pool the classes of vehicles and estimate one redesign cost and one scrap value across all vehicles classes. Separating things by classes yields similar results in terms of stability of the non-linear search. We find that provided we do not use the Nelder–Mead algorithm alone, we converge to the same place for both parameters, down to the third decimal point. Furthermore, when we allow the Nelder–Mead routine to converge and then start the Newton–Raphson rou-
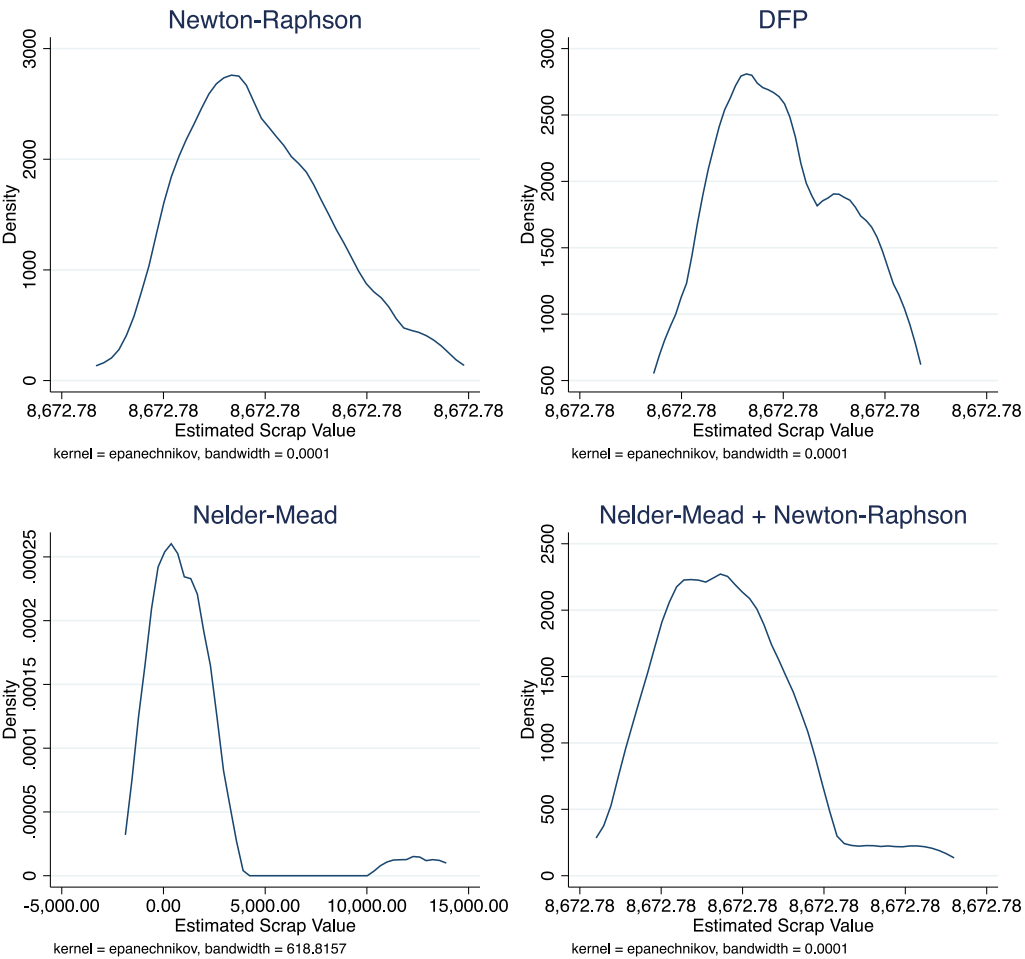
Fig. A.4. Estimated scrap value across starting values and algorithms.

tine at these parameter values, the Newton–Raphson routine leaves the space where the Simplex routine converged and goes to the lone extrema found by the Newton–Raphson and quasi-Newton algorithms. We take this as evidence that the Nelder–Mead routine terminates at points that are not minima.

Among the non-Nelder–Mead-only exercises, we analyzed the first-order conditions associated with those searches where Stata reports convergence. The mean Hessian-weighted gradient (in absolute value), among those for which convergence was reached, is $-1.53e-07$, while the maximum (minimum) is $3.18e-06$ ($-6.18e-06$). We therefore conclude that the first-order conditions are met. The Hessian is positive definite for all points, for which convergence is met, in the non-Nelder Mead estimates, implying the second-order conditions are also met. In addition, the condition number never exceeds

43.[38] Fig. A.1 shows the density of weighted-gradient, while Fig. A.2 shows the objective function across all non-linear search algorithms.

Given this exercise and using the "Smoke and Fire" analogy discussed in Knittel and Konstantinos (2014), we see no smoke and therefore have no reason to suspect any fire. Our results for the class-specific estimates are similar. For the final set of parameters used in the analysis, we still iterate over 9 different sets of starting values (500, 1000, and, 1500 for both parameters) and use the hybrid algorithm. We choose the set of parameter values corresponding to the lowest GMM objective value, but these do not differ at least for the first 11 significant digits.

Appendix B. Alternate specifications

Our main specification considers multi-product firms making dynamic redesign decisions. Here we present results from alternative assumptions in order to examine the channels of the model further. These alternatives include:

1. Single product firms
2. Multiproduct firms no characteristics
3. Multiproduct firms no exit

Figs. B.1 and B.2 display the willingness to pay for designs of different ages for each of these robustness exercises and our main specification. Here we repeat the dynamic estimation for each of the alternate specifications along side the main. Table B.1 presents these estimates and is best read from right to left. The right most column removes all firm decisions save for redesign, and moving left progressively adds firm incentives starting with the option to exit until we get to the left most column (our main specification) which accounts for redesign, exit, firm private valuation, multi-product firm pricing and controlling for vehicle characteristics.

Comparing Multi-Prod Firms with Firm Independence, we can see that the dynamic estimates are nearly identical when we assume each vehicle model is a single product firm. This is not surprising as the estimated demand model is comparable between the two assumptions, and the policy functions are unchanged. The assumption of single product firms does affect the magnitudes and patterns of the forward simulations, which has a noticeable effect on our scrap value estimates. It is reassuring that our redesign estimates are relatively stable to this assumption.

Additionally, we remove the option of firm exit from the dynamic model. This decreases our redesign estimates across the board. However, the patterns across vehicle classes are largely unaffected. The impact of removing exit from the model is also quite intuitive. Vehicles with large scrap values in the base model see the largest decrease in the estimated redesign cost as they substitute away from exit and into redesign in the forward simulations.

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[38] Judd (1998) argues that a condition number is small if its base 10 logarithm is about 2 or 3 for a computer that carries about 16 significant decimal digits. A condition number of 43 is well below this criterion.
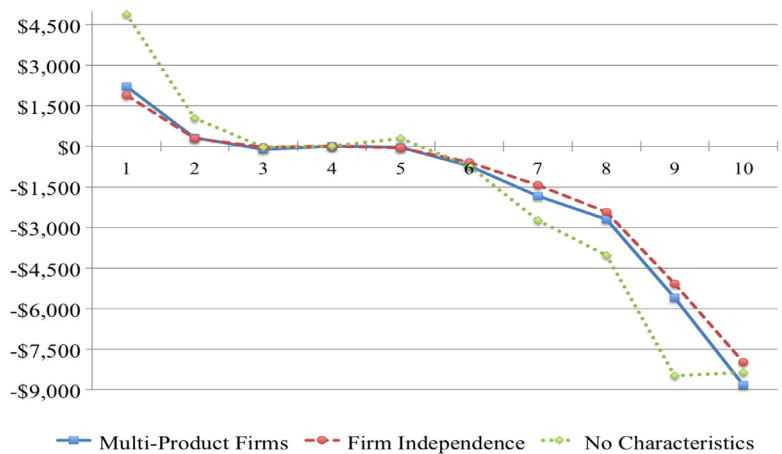
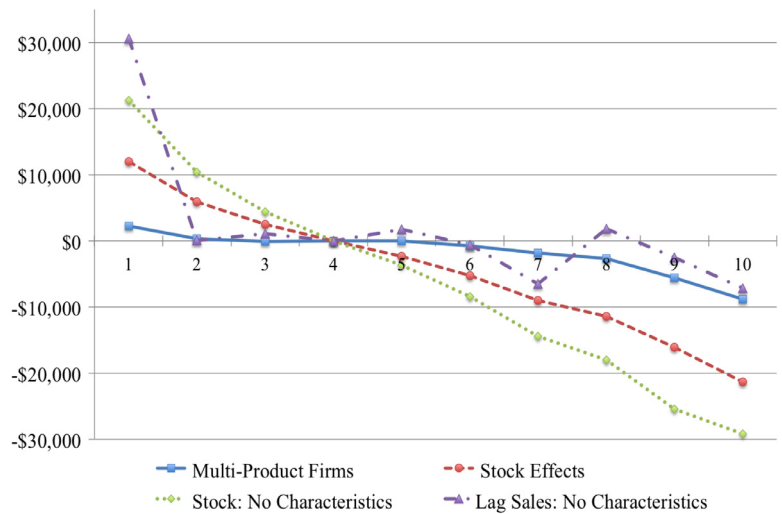**Fig. B.1.** Estimated age effects from demand model.

Fig. B.2. Estimated age effects from alternate demand models.

Finally, we explore the possibility that firms change their characteristics at and around redesigns by dropping characteristics from the demand model. This forces the age coefficients and demand error term to absorb the model's characteristics. This is by no means a preferred specification, but highlights the role of a model's age. Fig. B.1 demonstrates that without controls for characteristics, consumer willingness to pay for a redesign more than doubles. These demand effects are transferred to the dynamic estimates as larger redesign costs as firm redesign has larger stakes as it captures larger market shares.

To conclude, in Table B.2 we explore the issue of directly including our obsolescence measure, stock, in market share regressions. Clearly this variable is endogenous, as it enters with the opposite sign that we expect. It is reassuring that the inclusion of this

Table B.1
Estimates of dynamic parameters.

Type	Class	Multi-product firms with private payoffs			Multi-prod firms		Firm independence		Multi-prod firms: no characteristics		Multi-prod: no exit
		Red cost	Scrap Value	Priv value	Red cost	Scrap value	Red cost	Scrap value	Red cost	Scrap value	Red cost
	COMPACT	1119.95	4259.15	99.48	1509.64	2657.38	1493.96	2603.51	1970.74	4448.54	851.98
Car	FULL	1283.98	5576.46	299.60	967.70	1230.78	948.42	1303.93	1214.24	2176.13	542.07
	MID	1657.51	8305.98	499.09	963.49	3178.37	955.66	3064.66	1156.09	4437.48	599.49
	PU	3049.22	8169.17	496.91	1852.04	3468.40	1809.70	3675.97	2077.23	4344.24	1297.79
Truck	SUV	1320.91	5325.17	381.30	635.24	164.41	627.52	207.75	746.31	545.83	654.12
	VAN	1712.67	3784.82	159.76	1073.79	2237.76	1051.66	2142.04	1159.71	3308.06	839.09
Luxury	SPORT	860.34	5852.86	431.07	171.53	126.40	170.42	139.86	185.61	210.05	158.57
	LUX	1986.21	20267.54	1690.63	170.15	990.43	170.30	1028.98	201.28	1471.75	133.19

Table B.2
Market share regressions: exploring stock effects.

Characteristics	$ln(s_{jt}) - ln(s_0)$		
	(1)	(2)	(3)
$Price$ ($1000 in'85$)	−0.073***	−0.054***	0.002
	(0.010)	(0.010)	(0.002)
$log(s_{j/g})$	0.411***	0.184**	0.030
	(0.073)	(0.078)	(0.019)
$Miles/\$$	0.282***	0.373***	0.360***
	(0.104)	(0.096)	(0.028)
$\frac{HP}{Weight}$	1.065***	0.613**	−0.212***
	(0.281)	(0.251)	(0.064)
$log(Size)$	1.437***	0.978***	0.100
	(0.378)	(0.327)	(0.082)
$log(Engine\ displacement)$	0.443*	0.410*	0.138**
	(0.251)	(0.233)	(0.056)
$Redesign$	0.374***	0.513***	0.362***
	(0.075)	(0.085)	(0.050)
$Age = 1$	0.456***	1.293***	
	(0.133)	(0.179)	
$Age = 2$	0.679***	1.477***	0.093*
	(0.130)	(0.166)	(0.051)
$Age = 3$	0.643***	1.292***	0.101**
	(0.127)	(0.146)	(0.044)
$Age = 4$	0.653***	1.158***	0.084*
	(0.127)	(0.132)	(0.044)
$Age = 5$	0.651***	1.032***	0.102**
	(0.127)	(0.124)	(0.045)
$Age = 6$	0.597***	0.873***	0.076*
	(0.124)	(0.119)	(0.045)
$Age = 7$	0.505***	0.672***	0.019
	(0.119)	(0.108)	(0.052)
$Age = 8$	0.440***	0.538***	0.078
	(0.110)	(0.105)	(0.052)
$Age = 9$	0.222**	0.288***	0.050
	(0.110)	(0.099)	(0.065)
$Stock$		0.170***	
		(0.033)	
$log(Sales_{t-1})$			1.306***
			(0.071)
$log(Sales_{t-2})$			−0.298***
			(0.067)
$log(Sales_{t-3})$			0.055
			(0.040)
$log(Sales_{t-4})$			−0.076***
			(0.026)
R^2	0.626	0.613	0.937
N	4831	4831	3168

Note: Standard errors clustered by model are in parentheses, * $p< 0.10$, ** $p< 0.05$, *** $p< 0.01$.

variable does not affect the pattern of our age coefficients. In Column 3, we demonstrate that the stock effect is dominated by the endogenous relationship between lagged sales and current market shares making it a poor choice for inclusion in our demand model.

References

Bajari, P., Benkard, C., Levin, J., 2007. Estimating dynamic models of imperfect competition. Econometrica 75, 1331–1370.

Berry, S., 1994. Estimating discrete-choice models of product differentiation. Rand Journal of Economics 25, 242–262.

Berry, S., Levinsohn, J., Pakes, A., 1995. Automobile prices in market equilibrium. Econometrica 63, 841–890.

Blonigen, B.A., Soderbery, A., 2010. Measuring the benefits of foreign product variety with an accurate variety set. Journal of International Economics 82, 168–180.

Broda, C., Weinstein, D., 2006. Globalization and the gains from variety. Quarterly Journal of Economics 121, 541–585.

Chen, J., Esteban, S., Shum, M., 2013. When do secondary markets harm firms? American Economic Review 103, 2911–2934.

Chevalier, J., Goolsbee, A., 2009. Are durable goods consumers forward-looking? Evidence from college textbooks. The Quarterly Journal of Economics 124, 1853–1884.

Coase, R., 1972. Durability and monopoly. Journal of Law and Economics 15, 143.

Doraszelski, U., Satterthwaite, M., 2010. Computable Markov-perfect industry dynamics. The RAND Journal of Economics 41, 215–243.

Esteban, S., Shum, M., 2007. Durable-goods oligopoly with secondary markets: the case of automobiles. The RAND Journal of Economics 38, 332–354.

Feenstra, R.C., 1994. New product varieties and the measurement of international prices. The American Economic Review 84, 157–177.

Fishman, A., Rob, R., 2000. Product innovation by a durable-good monopoly. The RAND Journal of Economics 31, 237–252.

Goettler, R.L., Gordon, B.R., 2011. Does AMD spur intel to innovate more? Journal of Political Economy 119, 1141–1200.

Gowrisankaran, G., Rysman, M., 2012. Dynamics of consumer demand for new durable goods. Journal of Political Economy 120, 1173–1219.

Grout, P., Park, I.-U., 2005. Competitive planned obsolescence. The RAND Journal of Economics 36, 596–612.

Iizuka, T., 2007. An empirical analysis of planned obsolescence. Journal of Economics & Management Strategy 16, 191–226.

Jeziorski, P., 2014. Effects of mergers in two-sided markets: the US radio industry. American Economic Journal: Microeconomics 6, 35–73.

Judd, K., 1998. Numerical Methods in Economics. MIT press.

Kalouptsidi, M., 2014. Time to build and fluctuations in bulk shipping. American Economic Review 104, 564–608.

Kim, M., 2013. Strategic Responses to Used-Goods Markets: Airbus and Boeing Since 1997. Working paper, Boston University.

Knittel, C.R., 2011. Automobiles on steroids: product attribute trade-offs and technological progress in the automobile sector. American Economic Review 101, 3368–3399.

Knittel, C., Konstantinos, M., 2014. Estimation of random-coefficient demand models: two empiricists' perspective. Review of Economics and Statistics 96, 34–59.

Miller, H., Laurence, J., 1974. On killing off the market for used textbooks and the relationship between markets for new and secondhand goods. Journal of Political Economy 82, 612–619.

Moral, M., Jaumandreu, J., 2000. Optimal Multiproduct Prices. An Application in the Automobile Market.

Nevo, A., 2003. New products, quality changes, and welfare measures computed from estimated demand systems. The Review of Economics and Statistics 85, 266–275.

Nichols, M.W., 1998. Advertising and quality in the U. S. market for automobiles. Southern Economic Journal 64, 922–939.

Petrin, A., 2002. Quantifying the benefits of new products: the case of the minivan. Journal of Political Economy 110, 705–729.

Porter, R., Sattler, P., 1999. Patterns of Trade in the Market for Used Durables: Theory and Evidence. NBER Working Paper.

Purohit, D., 1992. Exploring the relationship between the markets for new and used durable goods: the case of automobiles. Marketing Science 11, 154–167.

Ryan, S., 2012. The costs of environmental regulation in a concentrated industry. Econometrica 80, 1019–1061.

Srisuma, S., 2010. Estimation of structural optimization models: a note on identification. STICERD Discussion Paper Series, EM/2010/547.

Swan, P., 1970. Durability of consumption goods. The American Economic Review 60, 884–894.

Sweeting, A., 2013. Dynamic product positioning in differentiated product markets: the effect of fees for musical performance rights on the commercial radio industry. Econometrica 81, 1763–1803.

Waldman, M., 1993. A new perspective on planned obsolescence. The Quarterly Journal of Economics 108, 273–283.

Waldman, M., 1996. Durable goods pricing when quality matters. Journal of Business 69, 489–510.

Waldman, M., 2003. Durable goods theory for real world markets. The Journal of Economic Perspectives 17, 131–154.

Wollmann, T., 2014. Trucks without bailouts: equilibrium product characteristics for commercial vehicles. Chicago-Booth working paper.