Keeping it fresh: Strategic product redesigns and welfare

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ABSTRACT

Product redesigns happen across virtually all types of products. While there is substantial evidence that new varieties of goods increase welfare, there is little evidence on the effect of product redesigns. We develop a model of redesign and exit decisions in a dynamic oligopoly model (a la Bajari et al (2007)) and use it to analyse redesign activity in the U.S. automobile market. We find that automobile model designs become obsolete quickly in this market, leading to fairly frequent redesigns of models despite an estimated average redesign cost around $1 billion. Our model and estimates show that firm redesign decisions depend crucially on competition for market share through introductions of new redesigns, as well as internal incentives for planned obsolescence of the existing model design. Based on our structural model estimates and the simulated counterfactuals, we find that redesigns lead to large increases in welfare, as well as substantial profit for firms, due to the strong preferences consumers display for new model designs. We also 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%. 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.

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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. 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 creates an incentive for the firm to introduce a redesigned model of the product to limit the competition of the secondhand markets with its current product. This phenomenon 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), 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) determining exit and redesign decisions. Because the specification is tied to a structural model, we can also simulate counterfactual scenarios and tie our results back to 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 incentives to develop new designs to recapture declining market share is what we call the "obsolescence effect," 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 redesign effect". Based on our structural model estimates, we then simulate an entire set of counterfactuals that consider 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%. 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.

The high valuation that consumers put on newly-designed models drives fairly frequent redesigns and gives automobile manufacturers fairly substantial market power, with a 4-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.[1] This led to some surprising results, such as prices being driven to marginal cost. Recent papers have relaxed many assumptions (such as perfect substitutability between old and used goods), but can then derive a wide variety of predictions. 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 ambiguous conclusions obtain even though these studies invariably consider the case of a monopolist producer.[2] 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.

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 Sat-

[1]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.

[2]An exception is Grout and Park (2005).

tler (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. (2008) 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. 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 is perhaps Iizuka (2007) and Kim (2013). Iizuka (2007) estimates the factors that affect when a new edition of a textbook is introduced. The hazard-model analysis finds significant evidence for a planned obsolescence effect, as greater used textbook sales and age of the textbook make a new edition more likely. However, there is no evidence for competitive effects 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. Kim (2013) also combines a discrete choice model with a two-step approach similar to Bajari et al. (2007) 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 focus is on new products. Our paper differs from these by examining more concretely the relative effects of redesign competition versus planned obsolescence 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) and 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 descriptive information on the patterns of redesign of automobile models we find in our data. In sections 3 and 4, we construct a dynamic model of redesign and competition in the automobile market, and estimate the model's parameters. 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, we next provide basic information on how automobile manufacturers redesign vehicles, as well as key features of the empirical patterns we see in the data we have on redesign activity.

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 its interior and exterior.[3] 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.[4] We focus on redesigns of models rather than minor updates that can occur annually, typically termed "refreshings" or "facelifts."[5] Redesigns receive

[3] 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 percent per year because of technological improvements.

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

[5] 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.

substantial attention by industry magazines, trade journals, and even popular media, while refreshings receive relatively little attention, even in trade journals. As a result, 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 sometimes be over $1 billion.[6] Our estimates below are quite consistent with this, averaging $750 million 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 (Design Prob) 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. Figure 1 documents market shares and timing of redesign patterns for the top-selling models by various class of vehicles. A number of interesting patterns emerge. First, redesign timing varies considerably across class of vehicle (e.g., compact cars redesign on average more frequently than vans), across models (e.g., the Audi A4 is redesigned much more frequently than the other top-selling luxury vehicles) and even over time for the same model. The latter fact importantly establishes that automobile manufacturers do not generally follow a fixed-year schedule for their redesigns (also see Figure 2).

Second, there are interesting patterns in market shares with the timing of redesigns that

[6]See http://www.forbes.com/2006/03/31/spring-luxury-cars_cx_dl_0403feat.html

may be suggestive of internal and external strategic considerations. For example, the market share of the top-selling van, the Dodge Caravan, sees a big shift up in a number of years after a redesign with a fall off in market share as the model ages, creating an oscillating pattern. Also in the van market, the Dodge Caravan's redesigns occur more rapidly towards the end of our sample as it starts to lose significant market share to new entrants, suggesting possible strategic responses to the success of these rivals.[7]

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

The auto industry is made up of a handful of firms overseeing a number of brands that each produce a set of models (varieties). We are foremost interested in modeling the role of redesign in the dynamics of competition between each model and its competitors. We therefore treat each model as an individual entity maximizing its own payoffs. As in Sweeting (2007), we are assuming away firms internalizing a redesigning model's cannibalization of demand for its other models for tractability. Denote each firm's model by j. These models fall into a particular class of vehicle g.

Each firm makes decisions at times $t = 1, ..., \infty$ of which actions to take, given current states, in order to compete in the oligopolistic market. In our model, we specify three different sets of states which firms face—the direct effects of their model's age, the indirect (obsolescence) effects of the model's age, and the competitive redesign effects in response to their direct competitors' (re)designs. The full set of states in period t is denoted as $\psi_{jt} = \psi_{jt}(d_{jt}, o_{jt}, c_{jt}) \in S \subset \mathbb{R}^L$. The direct effects, d_{jt}, include age of the current design,

[7] There is certainly anecdotal evidence for such strategic responses as well. For example, according to Lassa (2010), the radical redesign of the 2006 Honda Civic caused a one-year delay by Toyota in its redesign of its Corolla model, as it scrambled to revamp its redesign in response.

which equals unity for a newly redesigned model and increases by one each period the model is sold, and an indicator for redesign. Obsolescence states, o_{jt}, are meant to capture the potential internal incentive to obsolesce the secondary market for the model, which we control for by constructing the total stock of units of the current model sold in previous periods: $Stock_{jt} = \sum_{t=1}^{t} \mathbb{1}(Design_{jt} = Design_{jt-1}) * q_{jt-1}$. Competitive redesign effects, c_{jt}, represent the external pressure to redesign due to competing rival models' redesign activities. We proxy for these effects using the average age of competing models and total redesigns of models by competitors within the model's class. 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.[8]

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 firm j takes no action to change a model 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 this model next period, in $t+1$ the age of the model is reset to unity and stock 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 ($AgeComp_{gt}$) increases by one, and total competitor redesigns equals zero ($TotRedesign_{gt} = 0$). Firms that exit receive a value to scrap their model, and cannot reenter the market.[9]

Firm j's profits in t as a function of current actions and states is defined by $\Pi_{ij}(\boldsymbol{a}_t, \boldsymbol{\psi}_t)$. Firms dynamically optimize the present value of current and future profits,

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

[8]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.

[9]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.

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 t, which depends on the accompanying set of states $\boldsymbol{\psi}_t$. Our goal is to estimate the vector θ that rationalizes observed firm behavior. This vector is defined $\theta = [\theta_X, \theta_R]$, where the parameters θ_X and θ_R capture the value of exit and cost of redesign, respectively.

To estimate the dynamic parameters, we follow the methodology developed by Bajari et al. (2007), which proceeds in three steps. First, we estimate static behavior, which includes 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. Third, we perturb the policy rules and resimulate the markets in order to estimate the parameters that rationalize our observed market outcomes. We now describe these three steps in more detail.

3.1. The Static 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 (1994) for specifying the demand structure over 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,

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

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 $\sigma \in [0, 1]$ such that, 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 x_j, p_j and ξ_j, respectively.

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

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

where $D_g \equiv \sum_{j\in\Im_g} e^{\frac{\delta_j}{1-\sigma}}$. 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,

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

We address the endogeneity of price as Berry et al. (1995) suggest with instruments drawn from the characteristics of a model's competitors.

Static profits are calculated each period from the solution of the nested logit demand discussed above, and Bertrand competition. Static profits each period are,

$$\pi_{jt}(\boldsymbol{p}_t,\boldsymbol{x}_t,\boldsymbol{\psi}_t,\xi_t;\sigma,\alpha) = (p_{jt} - mc_{jt})Ms_{jt}(\boldsymbol{p}_t,\boldsymbol{x}_t,\boldsymbol{\psi}_t,\xi_t;\sigma,\alpha),$$

where M is market size, defined as the total number of households in the US, and mc_{jt} are firm specific marginal costs. Given these assumptions, price must satisfy the first order condition

$$s_{jt}(\boldsymbol{p}_t,\boldsymbol{x}_t,\boldsymbol{\psi}_t,\xi_t;\sigma,\alpha) + (p_{jt} - mc_{jt})\frac{\partial s_{jt}(\boldsymbol{p}_t,\boldsymbol{x}_t,\boldsymbol{\psi}_t,\xi_t;\sigma,\alpha)}{\partial p_{jt}} = 0.$$

Optimal pricing, combined with our nested logit specification, yields price as marginal costs plus a markup:

$$p_{jt} = mc_{jt} + \frac{1-\sigma}{\alpha[1 - \sigma\bar{s}_{j/gt} - (1-\sigma)s_{jt}]}\ .$$

It is important to note how our obsolescence term, stock of prior production of the model, is specified in our empirical framework describing static demand and profits. The stock of prior production of any model provides consumers the potential option of purchasing a used automobile rather than a new one. Thus, used vehicles are part of the consumer's "outside" option in the model to buying a new automobile. As a result, prior stock does not appear as a direct term in an individual's utility derived from a model's attributes, unlike redesign and age-related variables. In other words, we assume that the stock of prior production is not an attribute of a model that directly affects a consumer's utility from consuming that particular model. It will affect the consumer's ultimate demand choice as they compare their utility levels from consuming this model versus that of the outside good, which includes used automobiles. Also note that it will appear as a state variable that directly affects a model's redesign decision, which we discuss more below.

Table 2 provides our estimates of the determinants of market share from our nested logit discrete choice demand specification. Column 1 provides OLS estimates of our base specification with the standard controls, which include the price of the model, the market share of the model within its own group, and physical attributes of the model—fuel efficiency, horsepower, torque, weight, width, seating, and interior size. This base specification has an R^2 of 0.806, with many of the variables statistically significant and expected signs. The price term is negative and statistically significant, even without yet controlling for endogeneity. Also, the estimates suggest that larger cars with lower horsepower increase the relative market share of the model.

In Column 2 we add variables to account for the age and redesign attributes of the model. Our estimates suggest that each additional year of a model's current design lowers its relative market share by nearly 3.4%. In column 5 we include a full set of age effects (minus the effect for age 10 years and older). These OLS estimates do not suggest that market share is differently affected by a redesign year.

In Columns 4 through 6 of Table 2 we provide 2SLS estimates of these same specifications. As expected, the coefficient on price becomes larger in magnitude after controlling for endogeneity. In addition, most of the physical attribute characteristics are also statistically significant and accord with that found by previous studies. Most notably, the coefficient on horsepower 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. Each additional year for a model decreases its relative market share by 4.9%, but there is now a 19.7% relative gain in a model's market share for the initial redesign year. We also estimate a less restricted model that includes a full set of dummy variables, minus the indicator representing cars models that are 10 years or older. We are able to identify the coefficient capturing a new model, from the redesign effect, because we also observe completely new models.[10] The age-effects model shows an interesting non-linearity in the lifecycle of a vehicle. Following a redesign, the first-year age effect is roughly 1.44, the demand effects falls by nearly .6 in the second year, but then stays relatively flat until it begins to fall again after year five.

These 2SLS estimates are our preferred model for estimating the static effects of redesign activity on relative market shares for a given history of redesigns in the market place. In order to understand how the history of redesigns evolves dynamically, we next specify and estimate the policy functions that explain 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 (cost) parameters governing these decisions in the following section.

[10] We have also estimated the even-more flexible model where we have separate year effects for entrants and redesigns, but we cannot reject equality for ages two onward. Therefore, we report the more parsimonious specification.

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,

$$R_{jt+1}(\sigma) = \gamma_d d_{jt} + \gamma_c c_{jt} + \gamma_o o_{jt} + \beta_R ln(\bar{s}_{j/g}) + \epsilon^R_{jt}.$$

In addition to a within-group market share control ($\bar{s}_{j/g}$), the probability of redesigning next period (R_{jt+1}) depends on the direct, obsolescence, and competitive effects of redesign—the state variables in our model.[11] The direct effects are proxied by the age of the model, the redesign competition effects are captured by the total redesigns by competitors in the current period and the average age of competitors, and the obsolescence effects are captured by the stock of previous production of the model. 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.

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 constant term, the log of the model's overall relative share within its automobile class and age of the model. We hypothesize that automobile manufacturers will focus their redesign efforts on automobile groups with larger shares of the automobile market and on older models. The coefficient on each variable is positive and statistically significant at the 1% significance level.

In Columns 2 through 4, we sequentially introduce the direct, competitive redesign, and obsolescence effects, respectively. The coefficients on these variables have the expected sign and all these variables, except total redesigns by competitors in the current period, 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

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

coming period. This is consistent with an obsolescence effect. The older the average age of a model's competitors, the less likely a model will redesign, providing evidence for a competitive redesign effect.

Columns 5 and 6 add various interaction and higher-order terms of our state variables. Many 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. The final column also adds 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 (direct, competitive redesign, and obsolescence) and their interactions are important for the redesign policy function. The independent effects of model age and stock are statistically significant at the 1% level, as well as some of the non-linear and interaction terms involving these variables. The competitive redesign effects come through as statistically important in their interactions with other variables, namely the interaction of competitors' average age with the stock variables.

We use Column 7 estimates as our optimal redesign policy function for the dynamic forward simulations we undertake below. To better interpret Column 7, Figure 4 fits a lowess curve through the predicted policy of redesign and displays the effect of a model's age, stock of past production, and competitors' average age on the probability of redesign by type of vehicle (passenger cars, trucks (including SUVs and minivans), and luxury vehicles). In general, we see that older models with higher stock are significantly more likely to redesign, but that there is substantial variation across vehicle class. The competitive redesign effects, seen in Panel (c), are highly nonlinear as they depend greatly on their interaction with the other states.

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,

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

We specify exit as a function of the same state variables as redesign and report our estimation results in Table 4 as we did for the redesign function in Table 3. We see that the direct effects work 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 4, 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 (Column 7) statistical significance of the many individual interaction terms for these effects are a bit below standard confidence levels. The obsolescence 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 a high stock model's accrued brand recognition is likely worth the investment by firms 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 Figure 4 for the redesign policy function, Figure 5 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.

4. Estimating the Dynamic Model

Estimating the dynamic model hinges on forward simulations of state variables. Using the preceding optimal policy functions of firms, we forward simulate the market as firms take actions dictated by these policies given transitions of the state variable. The second stage to be estimated 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,

$$
\begin{aligned}
V_j(\boldsymbol{a}_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t; \theta) =& \mathbf{W^1}(\mathbf{a_t}(\boldsymbol{\psi}_\mathbf{t}), \boldsymbol{\psi}_\mathbf{t}) + \mathbf{W^2}(\mathbf{a_t}(\boldsymbol{\psi}_\mathbf{t}), \boldsymbol{\psi}_\mathbf{t})) * \theta_\mathbf{X} - \mathbf{W^3}(\mathbf{a_t}(\boldsymbol{\psi}_\mathbf{t}), \boldsymbol{\psi}_\mathbf{t})) * \theta_\mathbf{R} \\
=& \mathbb{E}\left[\sum_{t=1}^{\infty} \beta^{t-1} \pi_{ij}(\boldsymbol{a}_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t)) \Big| \boldsymbol{\psi}_t\right] \\
&+ \mathbb{E}\left[\sum_{t=1}^{\infty} \beta^{t-1} X_{j,t+1}(\boldsymbol{a}_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t)\right] * \theta_X \\
&- \mathbb{E}\left[\sum_{t=1}^{\infty} \beta^{t-1} R_{j,t+1}(\boldsymbol{a}_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t)\right] * \theta_R \ .
\end{aligned}
$$

The present discounted value of static profits given each simulated strategy is $\mathbf{W^1}$. The present value of a firm's simulated actions, scrapping production and the costs of redesign, are $\mathbf{W^2} * \theta_\mathbf{X}$ and $\mathbf{W^3} * \theta_\mathbf{R}$, respectively. θ_R includes such costs as research and development expenditures for redesign, as well as costs from production line retooling and advertising to inform consumers of the new model. One concern may be that redesigns require significant planning and are on relatively inflexible schedules. However, discussion with 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 re-designs. And the data also bear out that there is significant variation in length of redesign, even over time within models. Therefore, we will allow a re-design the possibility of occurring in any period, and let the actual timing be borne out by policy functions.

Following Bajari et al. (2007), the dynamic model is estimated by choosing $\hat{\theta}$ to minimize the objective function,

$$
Q(\theta) \equiv \int \Big(min\big[0, V_j(\boldsymbol{a}_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t; \theta) - V_j(\boldsymbol{a}'_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t; \theta)\big]\Big)^2 \, dH(x).
$$

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

$$V_j(\boldsymbol{a}_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t; \theta) \geq V_j(\boldsymbol{a}'_t(\boldsymbol{\psi}_t), \boldsymbol{\psi}_t; \theta)$$

Plainly, observing actions a_{jt} implies that choosing a'_{jt} would have been suboptimal, and we minimize the error rate in order to rationalize the firm outcomes we observe.

4.1. Forward Simulation

We first construct value functions for each model-year observation by forward simulating expected profits from future actions given expected states. Following the estimated policy functions and implied transition of the state variables allows us to construct firms' expectations about future profits. Most of our state variables are constructed from market realizations (e.g., average age of competitors). Therefore, we assume that each model's expected states and actions are known for computational feasibility. As we forward simulate this allows us to look across the behavior expected by each firm to construct market conditions. We track each model's actions and static market outcomes over 50 simulated periods in order to construct value functions at each period for every firm.

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 $\bar{X} = 0.4$. 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 and 0.4. At a standard 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.

Applying the second stage estimator involves constructing value functions for alternative policies and the transitional dynamics that these alternatives imply. Bajari et al. (2007)

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. We thus draw $\epsilon \sim Uniform[0, 2]$ independently for the exit and redesign policies for 500 perturbed policies.[12] Using these perturbed policy functions we forward simulate each model's value function in parallel to the optimal path.

Table 6 presents our estimates of the dynamic parameters using the Bajari et al. (2007) technique. Our estimates suggest that redesign costs average nearly $1 billion across all types of vehicles. There is some heterogeneity across types of vehicles with redesign costs smallest for sport and compact cars cars at around $500 million to the largest for pick-ups at $1.3 billion. While automobile firms undoubtedly 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 $300-500M on a remodel. Finally, a private conversation with a former manager in one of the major U.S. automobile manufacturers suggest 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 estimated scrap values are estimated to be significantly smaller 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 from which to identify these estimates in our data, in contrast to the high frequency of redesigns, the focus of our study.

[12] We have investigated various forms of perturbations, and the resulting estimates are similar across either method.

5. Baseline 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 effects over time. Figure 6 provides baseline estimates of welfare in the model over time. Panel (a) of Figure 6 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. 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)),

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

such that the total utility from new auto purchases in period t is $\sum_g U_{gt}$. 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 values (or "Firm Value") for each model in our sample and then sum.

Figure 6 displays a number of important features of our the market. First, as shown in Panel (a), firm value is around \$2.5 trillion for many years in our sample, which means an average of about \$50 billion in annual firm value flow.[13] Panels (b), (c), and (d) of Figure 6 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" vehicles. There are a number of interesting observations that one can take from Figure 6 . First, firm value is high relative to consumer surplus (about a ratio of 4 to 1), suggesting that firms are extracting a significant amount of the total surplus in the automobile market.[14] 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.

[13]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.

[14]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.

Third, the truck and luxury segments of the market appear to have been more affected by the recent recession than the standard cars market.

Figure 7 further decomposes just 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 1990 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 car segment show a 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 estimated scrap value component is very small compared to the other two components and fairly volatile. Cars and trucks are estimated to have a significantly higher average scrap value than luxury vehicles.

6. Counterfactual: Obsolescence, Redesign Competition and Welfare

We can now also use our model to address our initial goals in the paper—an analysis of how the dynamic forces of redesign competition and obsolescence not only affect redesign expenditures, but ultimately firm profits and overall welfare.

We analyze how welfare changes when we intensify and reduce the impact of both of these channels. Doing this is somewhat complicated by the flexibility of our policy function. To see this, take the general form of our redesign policy function:

$$R_{jt+1}(\sigma) = \gamma_d d_{jt} + \gamma_c c_{jt} + \gamma_o o_{jt} + \beta_R ln(\bar{s}_{j/g}) + \epsilon_{jt}^R.$$

In the simple case where there is one state variable capturing redesign competition and one capturing obsolescence, and both γ_c and γ_o are positive, to intensify or reduce the effects of each channel, we could introduce two new parameters, δ_c and δ_o, defining the policy function as:

$$R_{jt+1}(\sigma) = \gamma_d d_{jt} + \delta_c \gamma_c c_{jt} + \delta_o \gamma_o o_{jt} + \beta_R ln(\bar{s}_{j/g}) + \epsilon^R_{jt}.$$

We could then analyze how welfare changes when we vary γ_c and γ_o. This exercise would identify the pair of γs that maximize total welfare; a $\gamma < 1$ would reduce the channel, while a $\gamma > 1$ would increase the channel.

Our redesign policy function is more flexible, and therefore more complicated, than this simple example. Two complications arise: sign changes across the γs and interaction terms. To see why sign changes across the parameters of the competitive redesign or obsolescence effects matter, suppose we had two variables capturing the redesign competition effects, c_{1jt} and c_{2jt}:

$$R_{jt+1}(\sigma) = \gamma_d d_{jt} + \gamma_{1c} c_{1jt} + \gamma_{2c} c_{2jt} + \gamma_o o_{jt} + \beta_R ln(\bar{s}_{j/g}) + \epsilon^R_{jt}.$$

Now suppose that $\gamma_{1c} > 0$, while $\gamma_{1c} < 0$. If we multiplied both variables by the same $\delta > 1$, this would tend to increase the probability of a redesign by making $\gamma_{1c} c_{1jt}$ more positive, but at the same time, it would tend to reduce the probability of a redesign by making $\gamma_{2c} c_{2jt}$ more negative. The net effect of this could be to increase or decrease the probability of a redesign, and δ would no longer carry the interpretation we seek.

This issue is easy to overcome. In our counterfactuals, we multiply by δ_j whenever γ_j is positive and divide by δ_j whenever γ_j is negative. Therefore, in the example above, a $\delta > 1$ would make both $\delta_c \gamma_{1c} c_{1jt}$ and $\frac{1}{\delta_c} \gamma_{2c} c_{2jt}$ more positive.

The second issue—the existence of interaction terms—cannot be completely accounted for and changes the interpretation of the δ_js slightly. To see the complication here, suppose our δ-augmented redesign policy function was:

$$R_{jt+1}(\sigma) = \gamma_d d_{jt} + \delta_c \gamma_c c_{jt} + \delta_o \gamma_o o_{jt} + \delta_c \delta_o \gamma_{oc} c_{jt} o_{jt} + \beta_R ln(\bar{s}_{j/g}) + \epsilon^R_{jt}.$$

Ideally, δ_c and δ_o scale the derivatives of the probability of a redesign with respect to the two channels. In this simple set up those derivatives are:

$$\frac{\partial R_{jt+1}(\sigma)}{\partial c_{jt}} = \delta_c c_{jt} + \delta_c \delta_o \gamma_{oc} o_{jt},$$
$$\frac{\partial R_{jt+1}(\sigma)}{\partial o_{jt}} = \delta_o o_{jt} + \delta_c \delta_o \gamma_{oc} o_{jt}.$$

With interaction terms, δ_c is present in both the derivative with respect to the redesign competition channel and the derivative of the obsolescence channel. If we interpret δ_c as magnifying the size of the redesign competition state variables, then the interaction terms do not present a problem. If, however, we want to interpret δ_c as magnifying the parameter estimates associated only with the redesign competition channel, then our set up is not ideal.

To identify welfare under different δ_js, we perform a grid search varying the size of the δ_js from 0 to 2 in 0.1 increments. We search for the pair of δ_js that maximize 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 δ_j^*s in each year.

We begin by summarizing our results by showing a contour plot of the sum of total welfare across each year in our sample. Figure 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. As one can see, the baseline scenario, where both parameters are at 1, is in a region where welfare is already fairly high relative to that when the parameters are perturbed. It is also clear that perturbations to reduce the responsiveness of the redesign policy function to either (or both) of the redesign competition or obsolescence effects results in major welfare losses, whereas perturbations to increase responsiveness of the redesign policy function 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 baseline sees relatively high welfare, our contour of counterfactuals suggests that welfare could be improved in this marketplace by moving southeast from the baseline to a region that represents a reduced redesign competition effect and a greater obsolescence effect. The black diamonds represent combinations of δ_js that maximize welfare in at least one single year, which we term our "optimal counterfactuals." These suggest that in the typical year, welfare is maximized by reducing the redesign competition channel by roughly 50 percent, but increasing the obsolescence channel by between 50 and 100 percent. The welfare difference between the optimal counterfactual and our baseline is roughly 3 percent. 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 Figure 8.

We can also use our simulations to show how consumer utility, firm value, and total welfare in these optimal counterfactuals compare to the baseline estimates in each year. It is possible that either firms or consumers can be made worse off in the optimal counterfactual, even if total welfare is a bit higher. And these comparisons may vary over time in the market. Figure 9 plots the welfare difference of the optimal counterfactual 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), (c), and (d). Under the optimal counterfactuals, firm value is higher in each year. In contrast, consumer utility under the optimal counterfactual can sometimes be lower than for our baseline scenario. Lower relative consumer utility in the optimal counterfactual is especially pronounced from 1991 to 1993 and from 2008 and 2009. The first of these periods was a macroeconomic downturn, while the second 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 (positive) welfare difference in the counterfactual relative to the baseline, while the car market segment has the smallest.

Finally, in Figure 10 we show the relative differences between the optimal counterfactual and the baseline for the components of firm value (profit from sales, redesign expenditures, and scrap values). As with Figure 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 panels. As shown above, the optimal counterfactual is consistently one where the competitive redesign channels are weakened and the obsolescence channels are strengthened. These should have opposite effects on how often firms redesign and, thus, total redesign expenditures. As seen in Figure 10, the weaker competitive redesign channel in the optimal counterfactual appears to dominate with respect to the effect on redesign expenditures, as they are lower in the optimal counterfactual relative to the baseline by 10%, or $20B, on average. In contrast, Panel (c) shows more exit in the optimal counterfactual. However the increase in exit is large in percentage terms (30% on average to a maximum of 400%) but small in relative value ($1B on average to a maximum of $5B). We interpret the change in firm behavior from the optimal perturbation as enhancing social efficiency by reducing inefficient redesigns coming from redesign competition, enhancing redesigns valued by consumers that come from obsolescence, and discontinuing weak varieties. Panel (a) demonstrates that the more efficient timing of redesigns results in very little change to profits from sales and consumer welfare. Welfare gains are thus realized as firms acquire significant savings by eliminating excess redesigns with minor distortions to the final goods market.

7. Secondhand Market Considerations

Our model and welfare analysis is clearly focused on the new automobile market. We do 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 counterfactual may be at the expense of used car value. Our framework admittedly does not explicitly model the secondhand market, as that goes beyond the scope of this paper, and 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 did the following. First, using auction data of secondhand vehicles, we estimated 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 manufacturer 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 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.[15]

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 counterfactual, 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 in both the baseline and counterfactual simulations are small when compared to the welfare losses in the new automobile market if we were to eliminate redesign.[16]

8. Conclusion

This paper builds the first empirical structural model of product redesign. 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

[15]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.

[16]Eliminating redesign in the baseline or counterfactual leads to anywhere from a 40%-50% loss in total surplus, which is approximately $1.5 trillion in our simulations.

recapture market share play an important role. Our counterfactual simulations find evidence that there is 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 redesign competition channel by roughly 50 percent, but increasing the obsolescence channel by between 50 and 100 percent. This would have a net effect of reducing redesign expenditures by about 10% and increasing welfare by 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 counterfactual has nearly six times the effect on consumer welfare as previous estimates of new variety introduction.

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A Appendix: 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 Metaxoglou (Forthcoming). Ultimately, we found that unless one uses the Nelder-Mead (Simplex) algorithm, convergence is always met in the same location (down to 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.[17] While Stata is more limited than alternative programs, such as Matlab, in terms of the options for undertaking the non-linear search, 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) 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 two dynamic parameters, we used nine different starting values (representing millions of dollars): -1100, -600, -100, 400, 900, 1400, 1900, 2400, and 2900. The intersection of these two sets yields 81 starting-value combinations for each algorithm.

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

Figures 13 and 14 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 routine 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) is 1.66e-06, while the maximum is 1.3e-04. We therefore conclude that the first-order conditions are met. The Hessian is positive definite for all points, implying the second-order conditions are also met. In addition, the condition number never exceeds 13.5.[18] Figure 11 shows the density of weighted-gradient, while Figure 12 shows the objective function across all non-linear search algorithms.

Given this exercise and using the "Smoke and Fire" analogy discussed in Knittel and Metaxoglou (Forthcoming), 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.

[18] 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 13.5 is well below this criterion.

B Tables and Figures

Table 1: Summary Statistics of Key Variables

Body	Class	Redesign	Rival Redesigns	Age	Design Age	Rivals	Price ($1000s)	Sales (1000s)	MPG	Wheel Base	HP	Weight (lbs)	Exiting Models
Car	SMALL	0.106	5.16	3.73	6.02	39.54	10.664	82.180	33.0	99.4	118	2570	0.094
	FULL	0.098	2.82	4.47	6.98	18.46	21.228	61.568	26.7	110.6	198	3567	0.077
	MID	0.108	4.39	3.59	6.25	30.77	18.200	100.834	28.4	107.0	176	3267	0.054
Truck	CUV	0.077	7.88	3.10	5.89	72.63	25.447	51.415	23.7	107.7	221	3899	0.021
	PU	0.098	2.56	4.63	8.40	15.66	15.521	165.257	20.8	127.1	190	4066	0.051
	SUV	0.085	5.20	4.19	7.61	49.87	25.021	56.101	19.4	109.8	218	4402	0.057
	VAN	0.073	2.79	5.73	9.18	24.23	17.768	56.671	21.4	121.1	180	4318	0.067
Luxury	LUX	0.121	7.18	3.65	6.21	55.61	30.138	27.806	26.1	106.8	223	3432	0.068
	SPORT	0.091	6.62	4.11	7.21	51.53	40.934	12.550	24.3	101.5	265	3462	0.066

Note: Values are averages across all years of the sample within vehicle classes.

Table 2: Market Share Regressions

Characteristics	$ln(s_{jt}) - ln(s_0)$					
	OLS			IV		
$Price$ (\$1000in'85)	-0.021^{***}	-0.021^{***}	-0.021^{***}	-0.095^{***}	-0.094^{***}	-0.099^{***}
	(0.004)	(0.004)	(0.004)	(0.035)	(0.035)	(0.034)
$log(s_{j/g})$	0.827^{***}	0.821^{***}	0.820^{***}	0.045	0.050	0.046
	(0.022)	(0.022)	(0.022)	(0.105)	(0.103)	(0.105)
$Miles/\$$	0.008^{**}	0.006	0.006	0.050^{***}	0.046^{***}	0.047^{***}
	(0.004)	(0.004)	(0.004)	(0.015)	(0.015)	(0.015)
$log(hp)$	-0.544^{***}	-0.591^{***}	-0.582^{***}	1.961	1.856	2.048
	(0.163)	(0.161)	(0.160)	(1.356)	(1.340)	(1.337)
$log(wheelbase)$	2.400^{***}	2.537^{***}	2.510^{***}	2.371	2.546^{*}	2.400
	(0.481)	(0.474)	(0.470)	(1.521)	(1.509)	(1.521)
$log(interiorsize)$	4.556^{***}	4.205^{***}	4.212^{***}	1.765	1.233	0.882
	(0.631)	(0.640)	(0.640)	(2.280)	(2.204)	(2.217)
$Redesign$		-0.003	0.067		0.197^{***}	0.602^{***}
		(0.024)	(0.047)		(0.059)	(0.104)
Age		-0.034^{***}			-0.049^{***}	
		(0.006)			(0.013)	
$Age = 1$			0.417^{***}			0.443^{**}
			(0.088)			(0.186)
$Age = 2$			0.441^{***}			0.797^{***}
			(0.083)			(0.192)
$Age = 3$			0.402^{***}			0.760^{***}
			(0.083)			(0.190)
$Age = 4$			0.401^{***}			0.766^{***}
			(0.082)			(0.189)
$Age = 5$			0.386^{***}			0.770^{***}
			(0.081)			(0.191)
$Age = 6$			0.355^{***}			0.723^{***}
			(0.080)			(0.183)
$Age = 7$			0.339^{***}			0.642^{***}
			(0.078)			(0.181)
$Age = 8$			0.266^{***}			0.555^{***}
			(0.067)			(0.160)
$Age = 9$			0.186^{**}			0.236
			(0.075)			(0.162)
R^2	0.806	0.811	0.811	0.277	0.297	0.284
N	4820	4820	4820	4820	4820	4820

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

Table 3: Redesign Policy

Controls	Logit Estimates of Pr[Redesign=1]						
Age	0.132***	0.164***	0.144***			0.193***	1.055***
	(0.034)	(0.033)	(0.033)			(0.035)	(0.123)
Age^2							−0.055***
							(0.009)
$Age = 2$				−3.332***	−3.357***		
				(0.453)	(0.462)		
$Age = 3$				−1.683***	−1.715***		
				(0.343)	(0.347)		
$Age = 4$				−0.812***	−0.843***		
				(0.250)	(0.252)		
$Age = 5$				−0.006	−0.037		
				(0.242)	(0.246)		
$Age = 6$				0.359	0.338		
				(0.239)	(0.241)		
$Age = 7$				0.270	0.250		
				(0.265)	(0.266)		
$Age = 8$				−0.032	−0.059		
				(0.274)	(0.275)		
$Age = 9$				0.201	0.177		
				(0.302)	(0.305)		
$TotRedesign$		0.035**	0.034*	0.047***	0.044**	0.035*	0.036*
		(0.017)	(0.017)	(0.017)	(0.020)	(0.020)	(0.020)
$\overline{AgeComp}$		−0.256***	−0.213**	−0.145*	−0.014	−0.020	0.091
		(0.085)	(0.083)	(0.075)	(0.080)	(0.097)	(0.535)
$\overline{AgeComp}^{\,2}$							−0.017
							(0.073)
$Stock$			0.058***	0.023*	0.030*	0.217***	0.611***
			(0.019)	(0.013)	(0.016)	(0.044)	(0.124)
$Stock \times Age$						−0.017***	−0.070***
						(0.005)	(0.019)
$Stock \times Age^2$							0.004***
							(0.001)
$Stock \times \overline{AgeComp}$						−0.005	−0.179***
						(0.016)	(0.060)
$Stock \times \overline{AgeComp}^{\,2}$							0.026***
							(0.009)
$log(s_{j/g})$	0.153***	0.203***	0.105**	0.186***	0.184***	0.063	0.149***
	(0.045)	(0.049)	(0.047)	(0.055)	(0.055)	(0.042)	(0.056)
Constant	−2.102***	−1.404***	−1.966***	−0.464	−0.732	−3.006***	−5.383***
	(0.229)	(0.384)	(0.367)	(0.469)	(0.515)	(0.418)	(1.054)
Group FEs	No	No	No	No	Yes	Yes	Yes
R^2	0.037	0.049	0.057	0.134	0.140	0.074	0.126
N	4514	4514	4514	4514	4514	4514	4514

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

Table 4: Exit Policy

Controls	Logit Estimates of Pr[Exit=1]						
Age	0.152***	0.169***	0.147***			0.157***	0.427***
	(0.028)	(0.024)	(0.023)			(0.026)	(0.056)
Age^2							−0.016***
							(0.004)
$Age = 1$				−3.560***	−3.553***		
				(0.486)	(0.485)		
$Age = 2$				−1.834***	−1.798***		
				(0.304)	(0.296)		
$Age = 3$				−1.001***	−0.977***		
				(0.252)	(0.249)		
$Age = 4$				−0.717***	−0.691***		
				(0.241)	(0.239)		
$Age = 5$				−0.394*	−0.378		
				(0.238)	(0.237)		
$Age = 6$				−0.143	−0.137		
				(0.231)	(0.233)		
$Age = 7$				−0.272	−0.276		
				(0.261)	(0.259)		
$Age = 8$				−0.788**	−0.816**		
				(0.327)	(0.337)		
$Age = 9$				−0.254	−0.293		
				(0.311)	(0.317)		
$TotRedesign$		−0.101***	−0.101***	−0.099***	−0.060*	−0.060**	−0.035
		(0.027)	(0.027)	(0.028)	(0.032)	(0.031)	(0.031)
$\overline{AgeComp}$		−0.314***	−0.279***	−0.196**	−0.122	−0.187	0.803
		(0.091)	(0.092)	(0.084)	(0.109)	(0.121)	(0.574)
$\overline{AgeComp}^{\,2}$							−0.118
							(0.078)
$Stock$			0.090***	0.084***	0.100***	0.130***	0.162
			(0.022)	(0.020)	(0.023)	(0.048)	(0.165)
$Stock \times Age$						−0.007*	−0.048***
						(0.004)	(0.011)
$Stock \times Age^2$							0.002***
							(0.000)
$Stock \times \overline{AgeComp}$						0.012	0.103
						(0.011)	(0.113)
$Stock \times \overline{AgeComp}^{\,2}$							−0.016
							(0.018)
$log(s_{j/g})$	−0.751***	−0.778***	−0.858***	−0.881***	−0.930***	−0.920***	−0.934***
	(0.062)	(0.062)	(0.071)	(0.078)	(0.083)	(0.075)	(0.081)
Constant	−0.751***	−5.731***	−6.267***	−5.055***	−5.311***	−6.694***	−9.492***
	(0.062)	(0.431)	(0.456)	(0.561)	(0.679)	(0.589)	(1.176)
Group FEs	−6.844***	No	No	No	Yes	Yes	Yes
R^2	(0.326)	0.203	0.213	0.246	0.262	0.231	0.249
N	5443	5443	5443	5443	5443	5443	5443

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

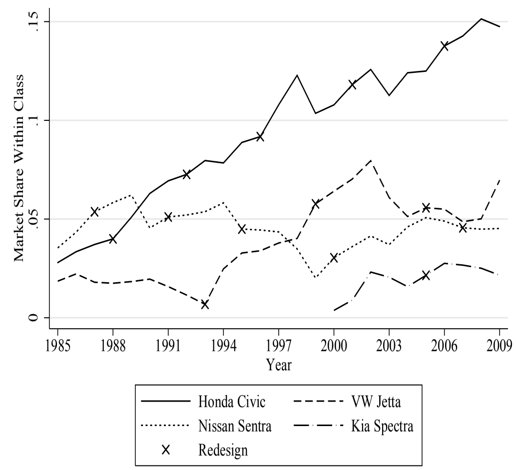
Table 5: Performance of Policy Functions

		Logit Policy Threshold ($\bar{R}$ or $\bar{X}$)						
	Sample	0.10	0.20	0.25	0.275	0.30	0.40	0.50
% Correct if								
Redesign = 1	100%	82.2%	46.2%	30.0%	22.0%	15.8%	4.9%	1.7%
Redesign = 0	100%	66.4%	86.7%	92.3%	94.5%	96.0%	99.2%	99.8%
Exit = 1	100%	12.4%	11.9%	11.9%	11.9%	11.9%	10.3%	9.8%
Exit = 0	100%	99.2%	99.4%	99.4%	99.4%	99.4%	99.5%	99.5%
Fraction of Sample								
Redesigned	9.8%	38.3%	16.5%	9.9%	7.1%	5.2%	1.2%	0.3%
Exited	6.9%	1.5%	1.3%	1.3%	1.3%	1.3%	1.1%	1.0%

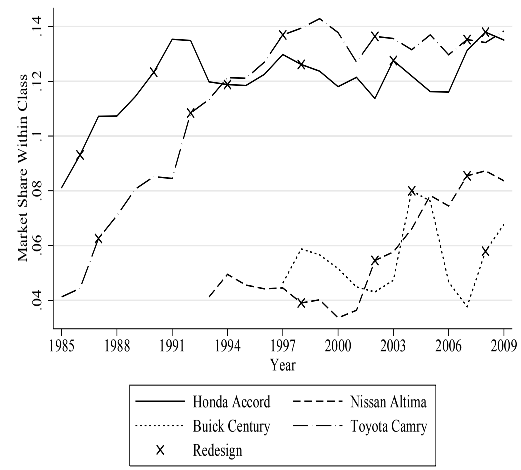
Table 6: Estimates of Dynamic Parameters

Type	Class	Redesign Cost ($M)	Scrap Value ($M)
Car	COMPACT	748.189	670.437
	FULL	610.789	339.629
	MID	865.390	913.242
Truck	PU	1320.444	1754.849
	SUV	700.290	607.463
	VAN	795.492	266.583
Luxury	LUX	614.002	117.170
	SPORT	505.648	20.170

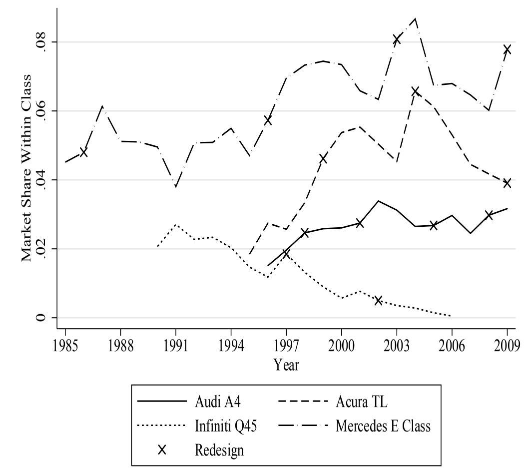
Figure 1: Market Structure Within Automobile Class



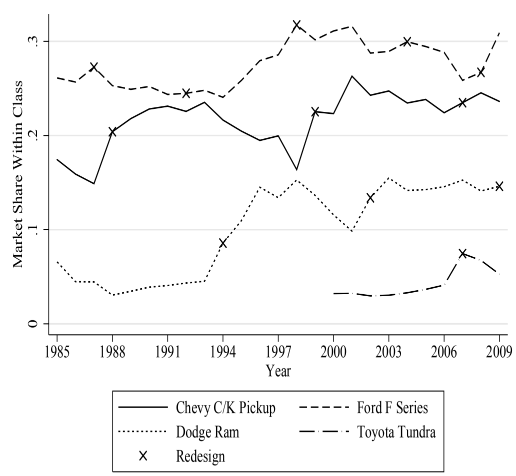
(a) Compact Cars



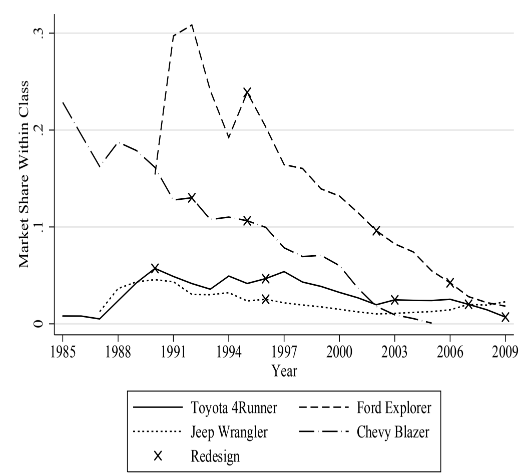
(b) Midsize Cars



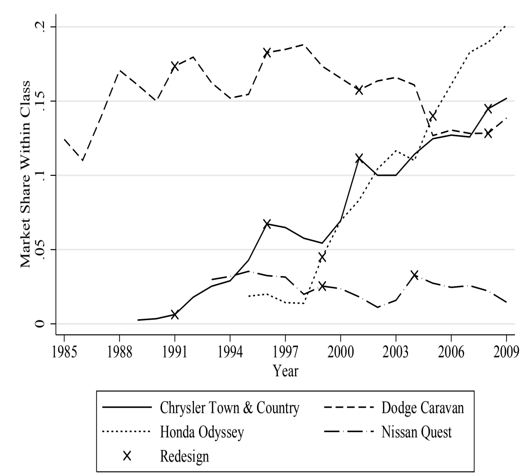
(c) Luxury Cars



(d) Pickups

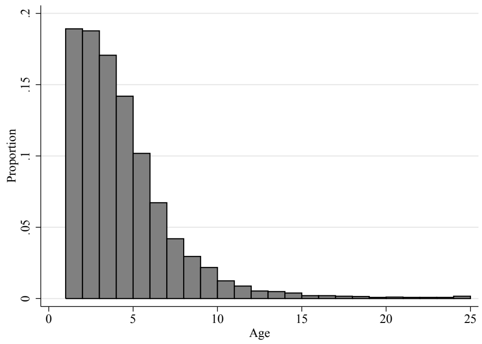


(e) SUVs

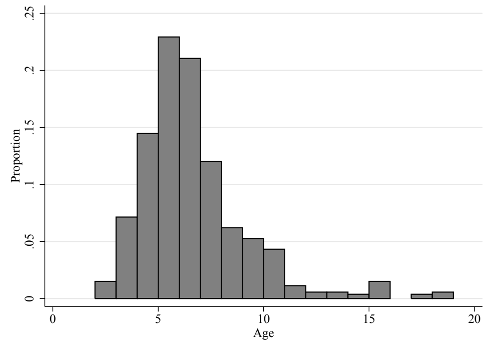


(f) Vans

Figure 2: Age Distribution

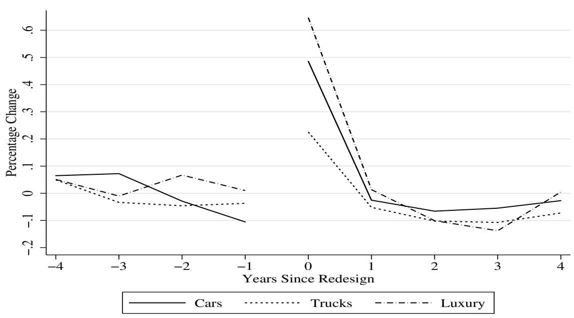


(a) Models Not Redesigning (Redesign = 0)



(b) Models Redesigning (Redesign = 1)

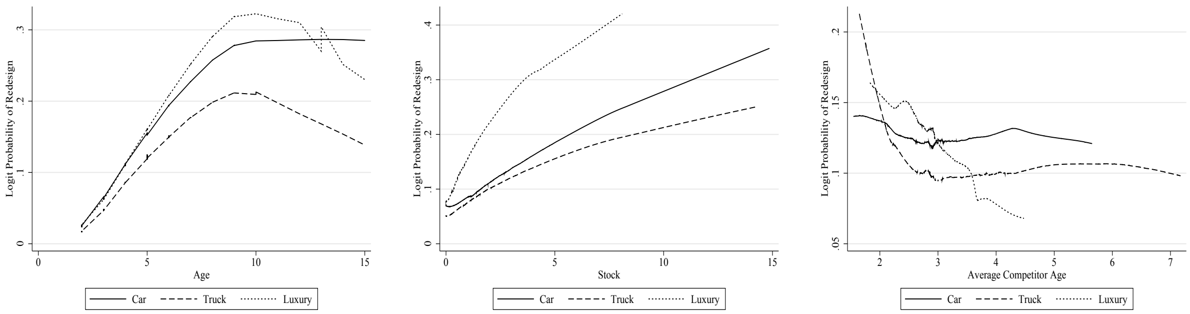
Figure 3: Design Lifecycle



(a) Redesign and Share

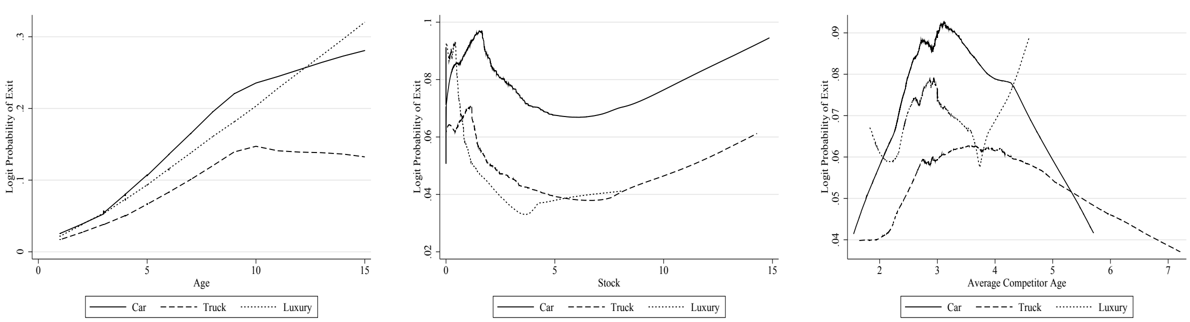
(b) Design Age and Share

Figure 4: Predicted Probability of Redesign



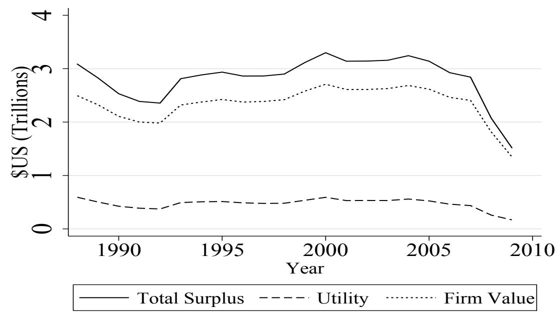
(a) Age Effects (b) Stock Effects (c) Competitor Age Effects

Figure 5: Predicted Probability of Exit

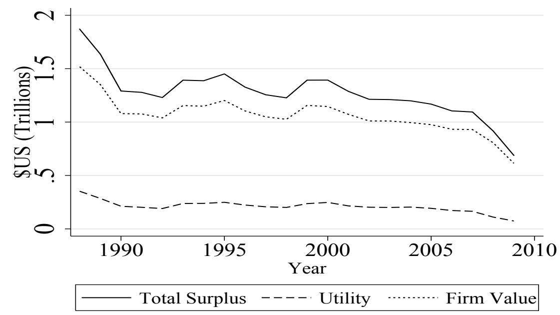


(a) Age Effects (b) Stock Effects (c) Competitor Age Effects

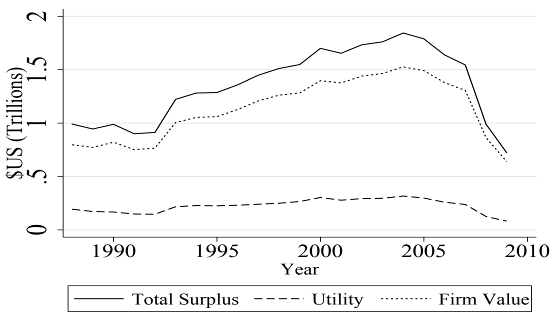
Figure 6: Welfare Baseline



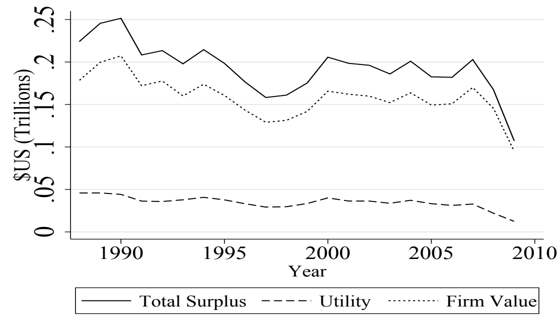
(a) Entire Market



(b) Cars

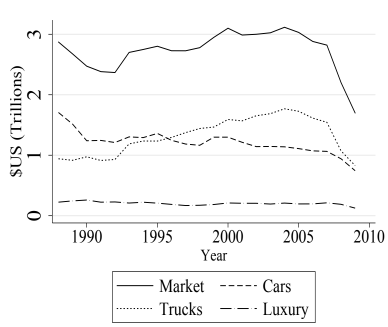


(c) Trucks

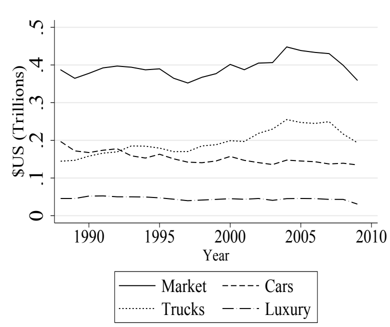


(d) Luxury

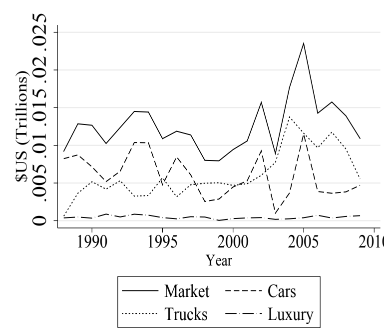
Figure 7: Decomposing Firm Value



(a) Profits from Sales ($\mathbf{W^1}$)

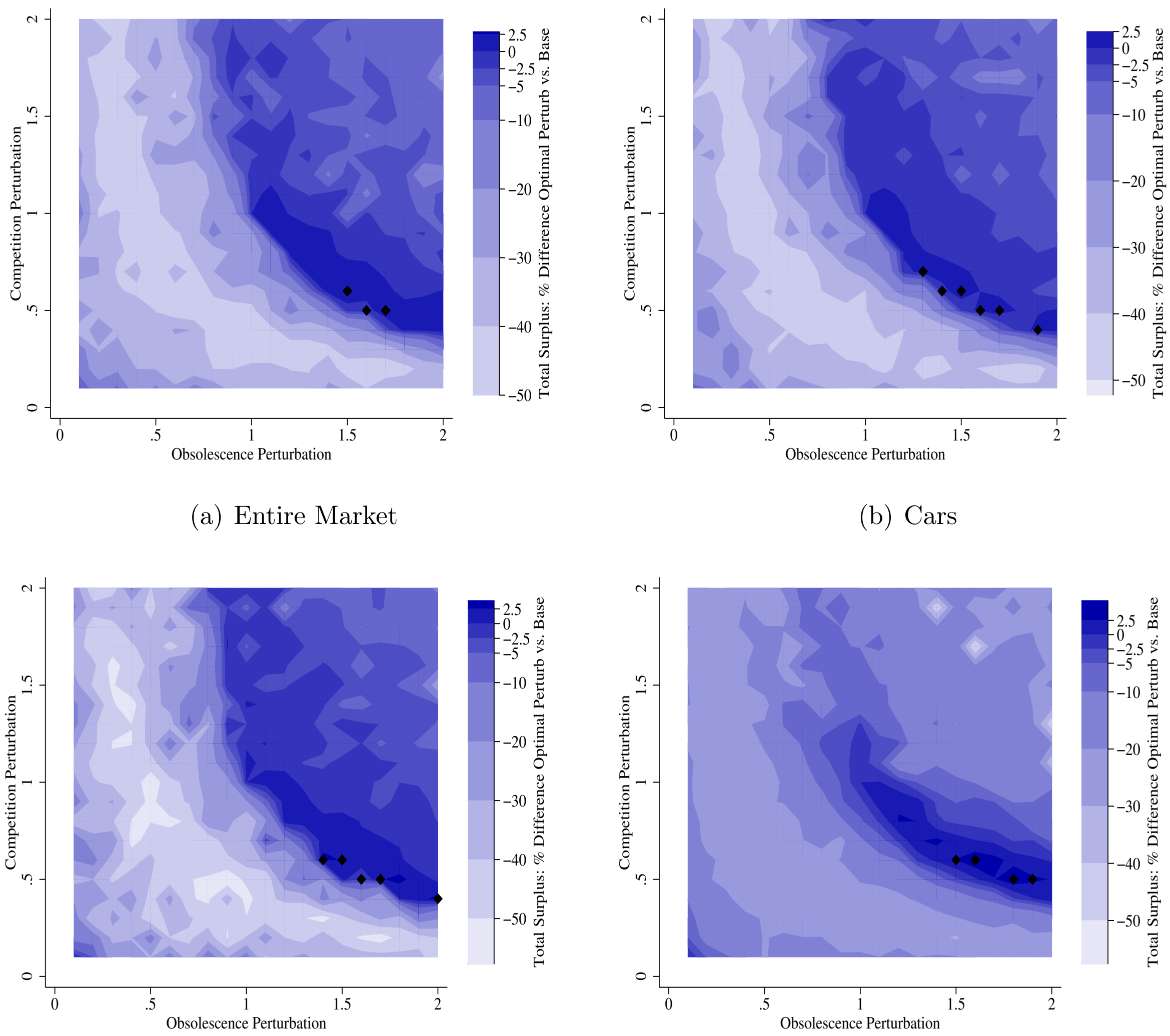


(b) Redesign Expenditure ($\mathbf{W^2} * \theta_\mathbf{R}$)



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

Figure 8: Mapping of the Welfare Differences Between Optimized Policy Functions Relative to Baseline Policy Functions



(a) Entire Market

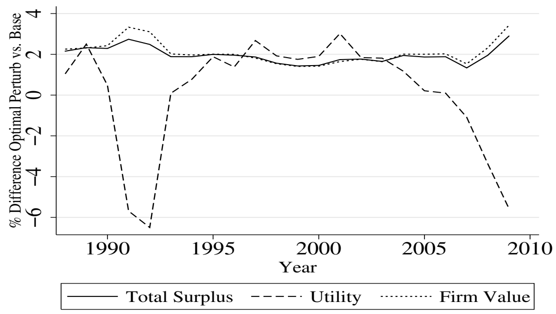
(b) Cars

(c) Trucks

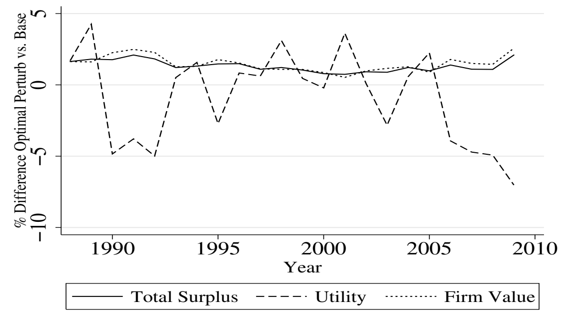
(d) Luxury

Note: $\diamond$ denotes the combination of perturbations that lead to the maximum total surpluses.

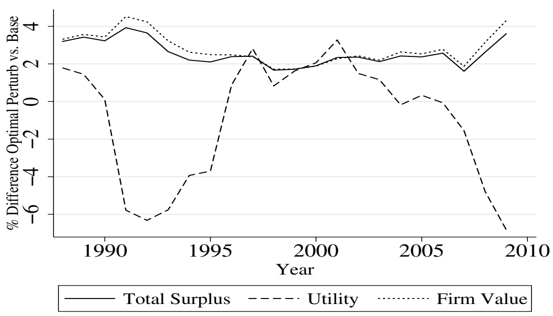
Figure 9: Welfare Components: Welfare Differences Between Optimized Policy Functions Relative to Baseline Policy Functions



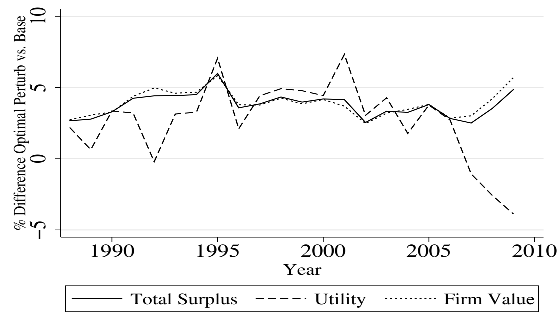
(a) Entire Market



(b) Cars

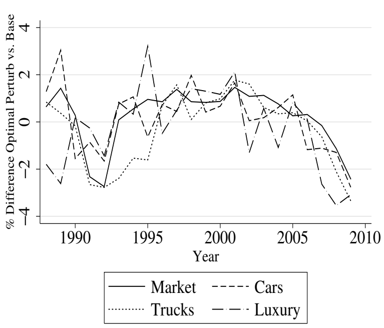


(c) Trucks

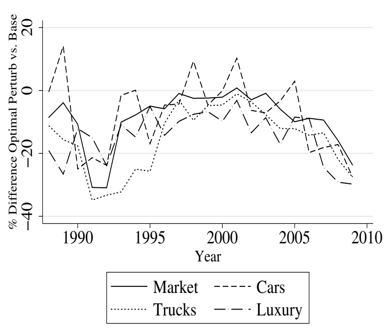


(d) Luxury

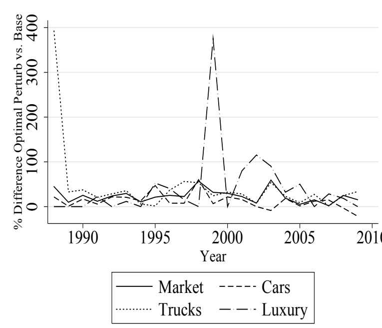
Figure 10: Decomposing Firm Value Components: Welfare Differences Between Optimized Policy Functions Relative to Baseline Policy Functions



(a) Profits from Sales ($\mathbf{W^1}$)



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



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

Figure 11: Gradient-weighted gradient of converged sets of parameters

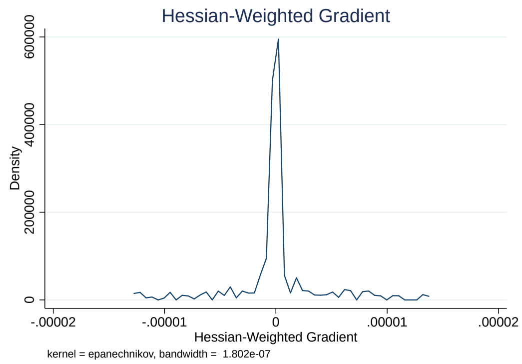


Figure 12: Objective function across all converged sets of parameters

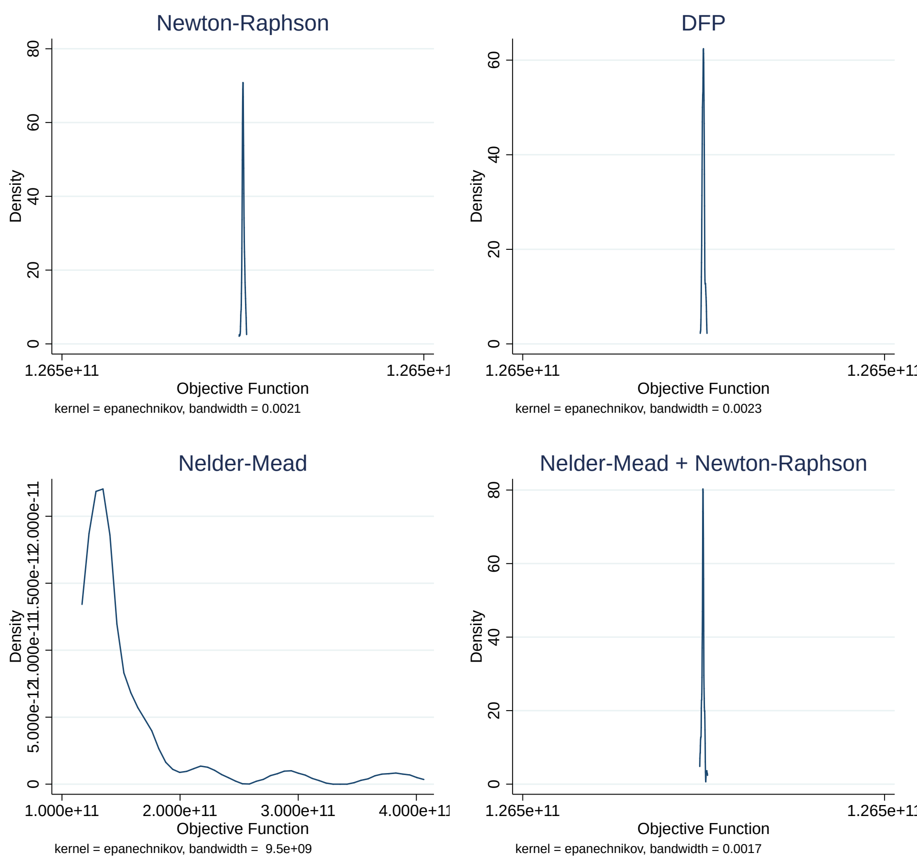


Figure 13: Estimated parameters across starting values and algorithms

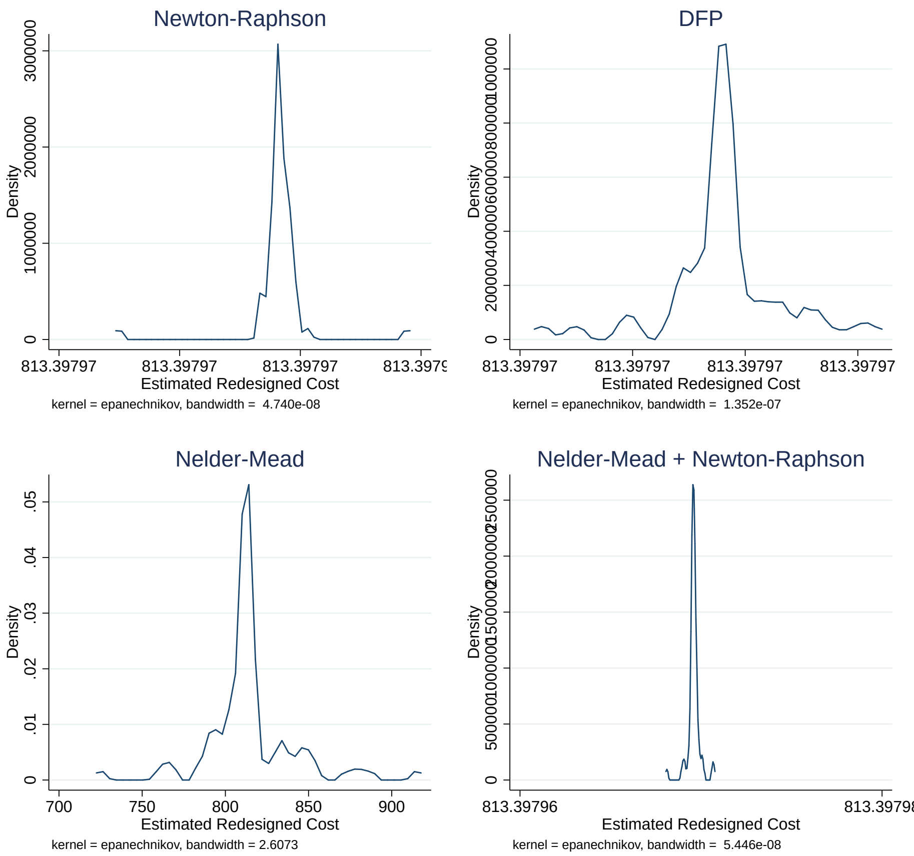


Figure 14: Estimated parameters across starting values and algorithms