The Evolution of Market Power in the US Automobile Industry*

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Abstract

We construct measures of industry performance and welfare in the U.S. automobile market from 1980-2018. We estimate a demand model using product level data on market shares, prices, and product characteristics, and consumer level data on demographics, purchases, and stated second choices. We estimate marginal costs assuming Nash-Bertrand pricing. We relate trends in consumer welfare and markups to market structure and the composition of products, like import competition and changes in vehicle characteristics. Although real prices rose, we find that markups decreased substantially and the fraction of total surplus accruing to consumers increased. Consumer welfare increased over time due to improving product quality and improved production technology.

JEL Codes: L11, L62, D43

1 Introduction

This paper analyzes the US automobile industry over forty years. During this period, the industry experienced numerous technological and regulatory changes and its market structure changed dramatically. Our goal is to examine whether these changes led to discernible changes in industry performance. Our work complements a recent academic and policy literature analyzing long term trends in market power and sales concentration from a macroeconomic perspective (De Loecker et al., 2020; Autor et al., 2020) with an industry-specific approach. Several papers and commentators point to a competition problem where price-cost margins and industry concentration have

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increased during this time period (Economist, 2016; Covarrubias et al., 2020). We find that, in this industry, the situation for consumers has improved noticeably over time. Furthermore, our estimates of price-cost margins for this industry differ from those computed using methods and data from the recent macroeconomics literature.

To estimate trends in industry performance in the U.S. new car industry, we specify a heterogeneous agent demand system and assume Nash-Bertrand pricing by multi-product automobile manufacturers to consumers to estimate margins and consumer welfare over time. The key inputs into the demand estimates are aggregate data on prices, market shares, and vehicle characteristics over time, micro-data on the relationship between demographics and car characteristics over time, micro-data on consumers' stated second choices, and the use of the real exchange rate between the US and product origin countries as an instrumental variable for endogenous prices.

We find that median markups as defined by the Lerner index ($L = \frac{p-mc}{p}$) fell from 0.32 in 1980 to 0.18 by 2018 (Figure 6). However, as we detail below, markups, although useful to proxy for market efficiency when products are unchanging, is a conceptually unattractive measure of market efficiency over long periods of time when products change. We leverage our model to consider trends in consumer and producer surplus directly. To quantify changes in welfare over time, we utilize a decomposition from Pakes et al. (1993a) to develop a measure of consumer surplus that is robust to changes in the attractiveness of the outside good. Our approach leverages continuing products to capture changes in unobserved automobile quality over time. However, it is not influenced by aggregate fluctuations in demand for automobiles e.g., business cycle effects such as monetary policy or changes in alternative transportation options. We find that the fraction of efficient surplus going to consumers went from 0.63 in 1980 to 0.79 by 2018 and that average consumer surplus per household increased by roughly \$20,000 over our sample period.

The increase in consumer surplus is predominantly due to the increasing quality of cars and improved production technology. We confirm the patterns in Knittel (2011) that horsepower, size, and fuel efficiency have improved significantly over this time period. We use the estimated valuations of these car attributes to put a dollar amount on this improvement. Furthermore, we use market shares of continuing products to estimate valuations of improvements in other characteristics such as electronics, safety, or comfort features that are not readily available in common data sets (e.g., audio and entertainment systems, rear-view cameras, driver assistance systems). Additionally we estimate improved production technology from variation in marginal cost over time controlling for product attributes. Counterfactuals which eliminate the observed increase in import competition or the increase in the number of vehicle models have moderate effects on consumer surplus. Counterfactuals which eliminate the increase in automobile quality and the technological improvements lead to the largest reduction of the observed consumer surplus increase.

A number of caveats are warranted for this analysis. First, our main results assume static Nash-Bertrand pricing each year and rule out changes in conduct, for example via the ability to tacitly collude. However, we will present a number of alternative assumptions on conduct, all of which indicate declining markups. Second, we do not model the complementary dealer, parts, or financing markets where the behavior of margins or product market efficiency over time may be different than the automobile manufacturers.

This paper is closely related to Hashmi and Biesebroeck (2016) who model dynamic competition and innovation in the world automobile market over the period 1982 to 2006. We focus on analyzing the evolution of consumer surplus and markups rather than modeling dynamic competition in quality. Furthermore, in addition to analyzing a longer time period, this paper uses microdata to estimate demand following Bordley (1993) and Berry et al. (2004), and uses a different instrumental variable to account for price endogeneity. Other papers which analyze outcomes in other industries over long time periods include Berndt and Rappaport (2001), Berry and Jia (2010), Borenstein (2011), Brand (2020), and Döpper et al. (2021).

2 Data

We compiled a data set covering 1980 through 2018 consisting of automobile characteristics and market shares, individual consumer choices and demographic information, and consumer survey responses regarding alternate "second choice" products. This section describes the data sources and presents basic descriptive information.

2.1 Automobile Market Data

Our primary source of data is information on sales, manufacturer suggested retail prices (MSRP), and characteristics of all cars and light trucks sold in the US from 1980-2018 that we obtain from Ward's Automotive. Ward's keeps digital records of this information from 1988 through the present. To get information from before 1988, we hand collected data from Ward's Automotive Yearbooks. The information in the yearbooks is non-standard across years and required multiple layers of digitization and re-checking. We supplemented the Ward's data with additional information, including vehicle country of production, company ownership information, missing and nonstandard product characteristics (e.g. electric vehicle eMPG and driving range, missing MPG, and missing prices), brand country affiliation (e.g. Volkswagen from Germany, Chrysler from USA), and model redesign years. Prices in all years are deflated to 2015 USD using the core consumer price index.

Product aggregation Cars sold in the US are highly differentiated products. Each brand (or "make") produces many models and each model can have multiple variants (more commonly called "trims"). Although we have specifications and pricing of individual trims, our sales data comes to us at the make-model level. Similar to other studies of this market, we make use of the sales data by aggregating the trim information to the make-model level, see Berry et al. (1995) Berry et al. (2004), Goldberg (1995), and Petrin (2002). We aggregate price and product characteristics by taking the median across trims.

Table 1: Summary Statistics

	Mean	Std. Dev.	Min	Max		Mean	Std. Dev.	Min	Max
Cars, N=6,130					**SUVs, N=2,243**				
Sales	52,122.99	72,758.06	10	473,108	Sales	51,553.00	66,898.86	10	753,064
Price	35.83	18.74	11.14	99.99	Price	40.44	14.99	12.75	96.94
MPG	22.66	6.81	10.00	50.00	MPG	18.02	5.03	10.00	50.00
HP	178.20	83.39	48.00	645.00	HP	232.30	74.98	63.00	510.00
Height	55.77	4.22	43.50	107.50	Height	69.01	4.37	56.50	90.00
Footprint	12,871.58	1,711.93	6,514.54	21,821.86	Width	13,789.91	1,791.43	8,127.00	18,136.00
Weight	3,182.40	640.32	1,488.00	6,765.00	Weight	4,245.77	855.08	2,028.00	7,230.00
US Brand	0.40	0.49	0.00	1.00	US Brand	0.40	0.49	0.00	1.00
Import	0.59	0.49	0.00	1.00	Import	0.59	0.49	0.00	1.00
Electric	0.02	0.14	0.00	1.00	Electric	0.02	0.12	0.00	1.00
Trucks, N=680					**Vans, N=641**				
Sales	141,039.59	184,425.07	12	891,482	Sales	65,357.38	64,649.39	11.00	300,117
Price	27.95	10.10	12.63	89.32	Price	31.43	5.54	17.79	47.65
MPG	17.83	4.37	10.00	50.00	MPG	17.92	5.06	11.00	50.00
HP	189.65	90.39	44.00	403.00	HP	188.18	63.79	48.00	329.00
Height	68.42	6.34	51.80	83.40	Height	74.35	8.21	58.85	107.50
Footprint	15,100.75	2,462.22	8,791.24	20,000.00	Length	15,173.34	1,882.28	11,169.30	21,821.86
Weight	4,049.63	1,113.84	1,113.00	7,178.00	Weight	4,270.26	793.09	2,500.00	8,550.00
US Brand	0.65	0.48	0.00	1.00	US Brand	0.71	0.45	0.00	1.00
Import	0.35	0.48	0.00	1.00	Import	0.29	0.45	0.00	1.00
Electric	0.00	0.00	0.00	0.00	Electric	0.00	0.06	0.00	1.00

Notes: An observation is a make-model-year, aggregated by taking the median across trims in a given year. Statistics are not sales weighted. Prices are in 2015 000's USD. Physical dimensions are in inches and curbweight is in pounds.

In Table 1 we display summary statistics for our sample of vehicles at the make-model-year level. An example of an observation is a 1987 Honda Accord. There are 6,107 cars, 2,213 SUVs, 676 trucks, and 618 vans in our sample.[1] The average car has 52,247 sales in a year and the average truck has 141,524 sales. Trucks and vans are more likely to be from US brands and less likely to be assembled outside of the US than cars and SUVs. Two percent of our sample has an electric motor (including hybrid gas-powered and electric only). We present a description of trends in vehicle characteristics in Section 3.

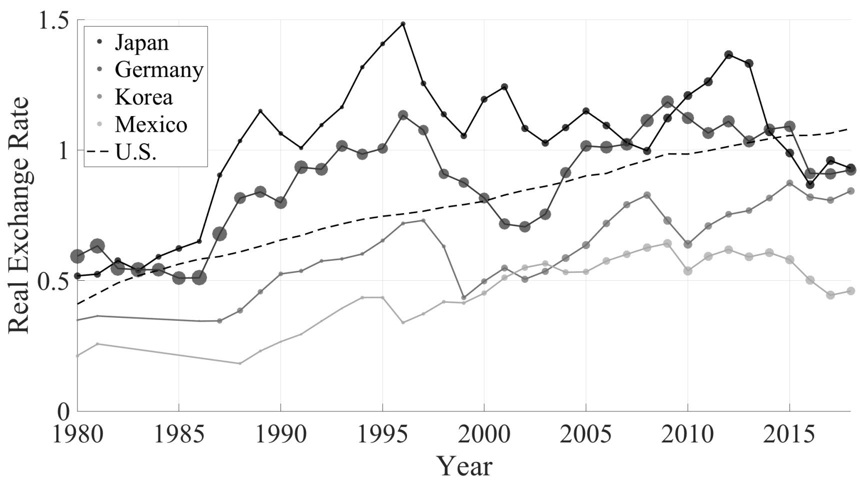
2.2 Price Instrument

To identify the price sensitivity of consumers, we rely on an instrumental variable that shifts price while being plausibly uncorrelated with unobserved demand shocks. We employ a cost-shifter related to local production costs where a model is produced. For each automobile in each year, we use the price level of expenditure in the country where the car was manufactured, obtained from the Penn World Tables variable $plGDP_e$, lagged by one year to reflect planning horizons. The price level of expenditure is equal to the purchasing power parity (PPP) exchange rate relative to the US divided by the nominal exchange rate relative to the US. As described in Feenstra et al. (2015), the ratio of price levels between a given country and the US is known as the "real exchange rate" (*Real XR*) between that country and the US. The real exchange rate varies with two sources

[1] We use Wards' vehicle style designations to create our own vehicle designations. We aggregate CUV (*crossover utility vehicles*) and SUV to our SUV designation. Truck and van are native Wards designations. We designate all other styles (sedan, coupe, wagon, hatchback, convertible) as car. Many models are produced in multiple variants. For example the Chrysler LeBaron has been available as a sedan, coupe, and station wagon in various years. However, no model is produced as both a car and an SUV, or any other combination of our designations, in our sample.

that are useful for identifying price sensitivities. First, if wages in the country of manufacture rise, the cost of making the car will rise, which will in turn raise the real exchange rate via the PPP rising. Therefore, the real exchange captures one source of input cost variation through local labor costs. Another source of variation is through the nominal exchange rate. If the nominal exchange rate rises, so that the local currency depreciates relative to the dollar, a firm with market power will have an incentive to lower retail prices in the US, thereby providing another avenue of positive covariation between the real exchange rate and retail prices in the US. Exchange rates were employed as instrumental variables for car prices in Goldberg and Verboven (2001), which is focused on the European car market, and in Berry et al. (1999a), along with wages. In Figure 1, we display the lagged *Real XR* for the most popular production countries, where the size of the marker is proportional to the number of products sold from each country and the black dashed line represents the U.S. price level.

Figure 1: Real Exchange Rates



Notes: Lagged real exchange rates from Penn World Table 9.2. Size of dots corresponds to number of sales by production country, except for USA.

We demonstrate the behavior of this instrumental variable in a simplified setup in Table 2. We estimate a logit model of demand, as in Berry (1994), first via OLS and then using two-stage least squares with *Real XR* as an instrumental variable for price. We include make fixed effects because brands assemble different models in different countries. For example, BMW assembles vehicles for the US market in Germany and the US, General Motors has produced US sold vehicles in Canada, Mexico, and South Korea (among other countries), and many of the Japanese and South Korean brands produce some of their models in the United States, Canada, and Mexico. Lacetera and Sydnor (2015) provide evidence that vehicle manufacturers maintain quality standards when producing the same model in different countries. The first column in Table 2 shows the first stage relevance of the instrumental variable. The sign is positive as predicted by the theory with a first stage F-stat of 13.603. We cluster the standard errors at the make level. The first stage implies a pass-through of Real XR to prices of 0.125, which is consistent with estimates in the literature (Goldberg and Campa, 2010; Burstein and Gopinath, 2014). The difference in the price coefficient in the last two columns demonstrates that employing the IV moves the coefficient estimate on price in the negative direction, which is expected because the OLS coefficient should be biased in the positive direction if prices positively correlate with unobserved demand shocks conditional on observable characteristics. Comparing the mean own price elasticities between the OLS and IV estimates confirms the importance of controlling for price endogeneity.

Table 2: **Logit Demand**

	First Stage	Reduced Form	OLS	IV
Real XR*	0.404 (0.110)	-0.686 (0.233)	– –	– –
Price	– –	– –	-0.324 (0.042)	-1.698 (0.610)
Height	-0.201 (0.047)	-0.079 (0.063)	-0.134 (0.065)	-0.421 (0.162)
Footprint	-0.111 (0.067)	0.331 (0.078)	0.304 (0.079)	0.142 (0.145)
Horsepower	0.773 (0.115)	-0.123 (0.067)	0.117 (0.066)	1.189 (0.484)
MPG	0.116 (0.036)	-0.077 (0.056)	-0.032 (0.061)	0.121 (0.118)
Weight	0.797 (0.111)	-0.470 (0.137)	-0.221 (0.135)	0.883 (0.545)
No. Trims	-0.116 (0.020)	1.099 (0.045)	1.063 (0.045)	0.902 (0.093)
Release Year	-0.013 (0.050)	-0.521 (0.060)	-0.522 (0.060)	-0.543 (0.093)
Sport	0.477 (0.091)	-0.684 (0.104)	-0.534 (0.101)	0.126 (0.330)
Electric	0.770 (0.176)	-1.052 (0.253)	-0.817 (0.242)	0.257 (0.570)
Truck	-0.408 (0.149)	-0.461 (0.097)	-0.600 (0.103)	-1.154 (0.358)
SUV	-0.104 (0.115)	0.558 (0.101)	0.516 (0.106)	0.381 (0.212)
Van	-0.250 (0.158)	0.041 (0.122)	-0.047 (0.137)	-0.385 (0.323)
Constant	3.666 (0.238)	-5.396 (0.214)	-4.555 (0.181)	0.831 (2.338)
Mean Own Price Elas.	–	–	-1.17	-6.12
Implied Pass-through	0.125 (0.026)			
First Stage F-Stat	13.603			

Notes: Unit of observations: year make-model, from 1980 to 2018. Number of observations: 9,694. All specifications include year and make fixed effects and a dummies for years since last redesign. Standard errors clustered by make in parentheses. All continuous car characteristics are in logs and price is in 2015 $10,000. Variables are standardized.
* Real exchange rate from *Penn Word Table 9.2*, variable `pl_gdp_con`.

2.3 Consumer Choices and Demographics

We collect individual level data on car purchases and demographics from two data sources: the Consumer Expenditure Survey (CEX) and GfK MRI's Survey of the American Consumer (MRI). These data sets provide observations on a sample of new car purchasers for each year, including the demographics of the purchaser and the car model purchased. CEX covers the years 1980-2005 with an average of $1,014$ observations per year. MRI covers the years 1992-2018 with an average of $2,005$ observations per year. We construct micro-moments from these data to use as targets for the heterogeneous agent demand model, following Goldberg (1995), Petrin (2002), and Berry et al. (2004). There are some general patterns from these data that motivate specification choices for the demand model. For example, that the average purchaser of a van having a larger family size suggests families value size more than non-families. That the average price of a car purchased by a high income versus low income buyer suggests higher income buyers are either less sensitive to price or value characteristics that come in higher priced cars more. That rural households are more likely to purchase a truck suggests different preferences for features of trucks by rural households.

In order to approximate the distribution of household demographics, we sample from the CPS, which contains the demographics information from 1980-2018 that we use from the CEX and MRI samples. Average household income (in 2015 dollars) increases from \$55,382 to \$81,375 from 1980 to 2018. Average household age increases from 46 to 51; average household size falls from 1.60 to 1.25; the percent of rural households decreases from 27.9 to 13.4. We will account for these trends by explicitly including evolving consumer heterogeneity in income, family size, and rural status as part of our model.

2.4 Second Choices

We obtain data on consumers' reported second choices from MartizCX, an automobile industry research and marketing firm. MaritzCX surveys recent car purchasers based on new vehicle registrations. The survey includes a question about cars that the respondents considered, but did not purchase. We use the first listed car as the purchaser's second choice. These data have previously been used, such as in Leard et al. (2017) and Leard (2019), and are similar to the survey data used in Berry et al. (2004).[2] After we merge with our sales data, we use second choice data from 1991, 1999, 2005 and 2015, representing 29,396, 20,413, 42,533, and 53,328 purchases, respectively.

In Table 3 we display information about second choices for many popular cars of different styles and features to give a sense for how strong substitution within vehicle style appears in the data. For each year, we display the modal second choice, the next most common second choice, and the share who report these two cars as second choices over the total responses for that car. For example, in 1991, the the Dodge Ram Pickup is the modal second choice among the respondents who purchased a Ford F Series. The Chevrolet CK Pickup is the second most popular second choice, and together, these two second choices make up 69 percent of reported second choices for the Ford F Series. From this sample of vehicles, second choices tend to be similar types of vehicles (i.e. trucks, cars, SUVs, vans). Also, there is substantial variation in the share that the two most frequent choices represent: for example, in 1991, the F Series and Dodge Ram represent 76 percent of reported second choices for the Chevrolet Silverado in 1999, but the Civic and Corolla only represent 22 percent of second choices for the Ford Focus in 2005. The generally strong substitution towards similar vehicles is crucial for identifying unobserved heterogeneity in the demand model we present in Section 2.

[2]The MaritzCX survey asks respondents about vehicles that the respondents considered but did not purchase. One of the questions is whether the respondent considered any other cars or trucks when shopping for their vehicle. Respondents answer this question either yes or no. For those that answer yes, the survey asks respondents to provide vehicle make-model and characteristics for the model most seriously considered.

Table 3: Second Choices, Selected Examples

Model and Year	**Modal Second Choice**	**Next Second Choice**	**(Modal + Next)/n**
1991 (N=29,436)			
Ford F Series	Dodge Ram Pickup	Chevrolet CK Pickup	0.69
Honda Accord	Toyota Camry	Nissan Maxima	0.32
Dodge Caravan	Ford Aerostar	Plymouth Voyager	0.28
Mercedes-Benz E Class	BMW 5 Series	Lexus LS	0.32
Toyota 4Runner	Ford Explorer	Nissan Pathfinder	0.58
Nissan 300ZX	Alfa Romeo 164	Chevrolet Corvette	0.35
1999 (N=20,413)			
Chevrolet Silverado	Ford F Series	Dodge Ram Pickup	0.76
Toyota Camry	Honda Accord	Nissan Maxima	0.38
Plymouth Voyager	Ford Windstar	Dodge Caravan	0.42
Audi A6	BMW 5 Series	Volvo 80	0.28
Chevrolet Tahoe	Ford Expedition	Dodge Durango	0.36
BMW Z3	Porsche Boxster	Mazda MX-5 Miata	0.42
2005 (N=42,977)			
Toyota Tacoma	Nissan Frontier	Ford F Series	0.35
Ford Focus	Toyota Corolla	Honda Civic	0.22
Honda Odyssey	Toyota Sienna	Chrysler Town & Country	0.71
Lincoln Town Car	Cadillac Deville	Chrysler 300 Series	0.44
Honda CR-V	Toyota Rav4	Ford Escape	0.38
Porsche Cayenne	BMW X5	Land Rover Range Rover	0.43
2015 (N=53,391)			
Ford F Series	Chevrolet Silverado	Ram Pickup	0.64
Toyota Prius	Honda Accord Hybrid	Honda CR-V	0.11
Toyota Sienna	Honda Odyssey	Chrysler Town & Country	0.64
Volvo 60	BMW 3 Series	Audi A4	0.16
Nissan Frontier	Toyota Tacoma	Chevrolet Colorado	0.69
Chevrolet Camaro	Ford Mustang	Dodge Challenger	0.46
Toyota Prius PHEV	Chevrolet Volt	Nissan Leaf	0.32

Notes: Data from Maritz CX surveys in 1991, 1999, 2005, and 2015. Vehicles selected are high selling vehicles that represent a range of styles and attributes.

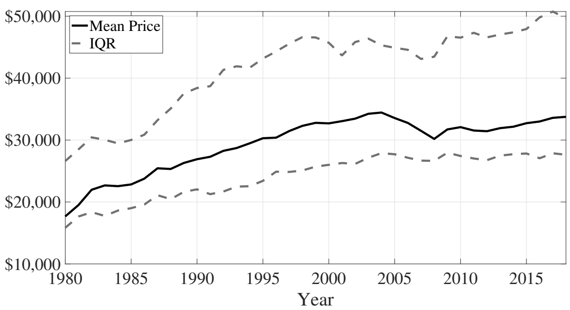
3 Empirical Description of the New Car Industry, 1980-2018

This section describes trends in the U.S. automobile industry from 1980 to 2018 related to market power and market efficiency. We first discuss changes in prices and market structure. Second, we discuss trends in product characteristics.

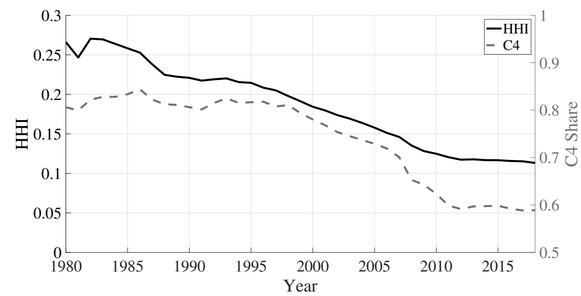
3.1 Prices and Market Structure

Real prices in the automobile industry steadily rose from 1980 to 2018. At the same time, concentration decreased. In Figure 2 we display these patterns. In panel (a), we document that the average manufacturer suggested retail price (MSRP) rose from around $17,000 in 1980 to around $36,000 in 2018 (in 2015 USD, deflated by the core consumer price index). The bulk of the change in average price occurred before the year 2000, although the upper 25 percent of prices continued to rise after 2000. At the same time, HHI measured at the parent company level fell from over 2500 to around 1200, see panel (b). The C4 index saw a similar decrease over the same time period, from around 0.80 to 0.58. In panel (c), we document the main source of decreasing concentration. While the total number of firms in this industry fell slightly from 1980 to 2018, there were about twice as many products in 2018 as there were in 1980. In 1980, the "Big 3" US manufacturers accounted for a large portion of sales, whereas by 2018, sales were more evenly dispersed among firms.

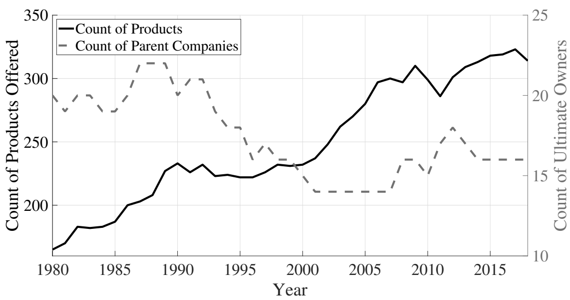
Figure 2: Prices and Market Structure, 1980-2018



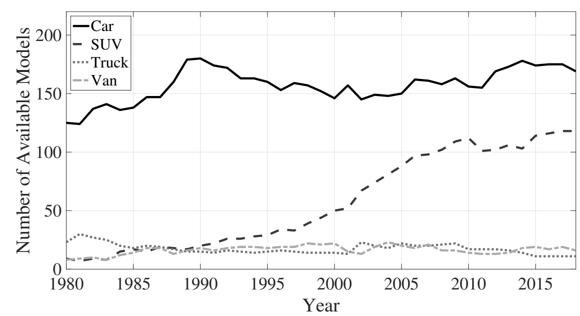
(a) Prices



(b) Measures of Concentration



(c) Products and Manufacturers



(d) Count of Products by Styles

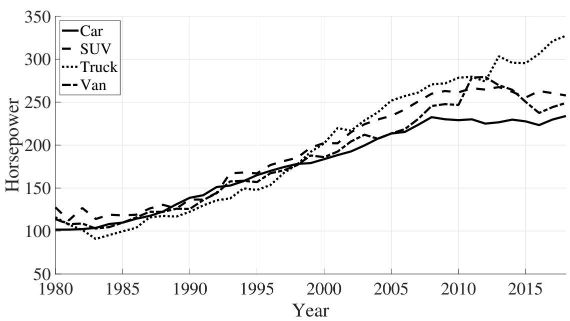
Notes: Panel (a): average price is not weighted by sales. Panel (b): HHI and C4 are defined at the parent company level, e.g. Honda is the parent company of the Honda and Acura brands. In Panel (c), the number of products corresponds to a model available in a given year in our sample. The style definitions referred to in Panel (d) are described in the text. Data is from Wards Automotive Yearbooks and the sample selection is described in the text.

3.2 Physical Characteristics of Vehicles

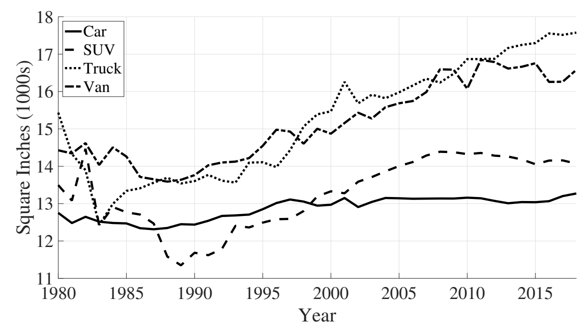
That prices rose while concentration fell might seem counterintuitive at first pass, however prices are also a function of physical characteristics, quality, and production technology. There are two main trends regarding the physical characteristics of cars. The first is the rise of the SUV, which was a nearly non-existent vehicle class in 1980 and by the end of our sample represented roughly half of all sales. Second, cars and trucks have become larger and more powerful without sacrificing fuel efficiency (Knittel, 2011).

The number of products available to consumers increased from 1980 to 2018. A major contribution to this change is the rise of SUV production, particularly smaller SUVs that are designed to compete with sedans. Our SUV category aggregates SUVs (typically larger vehicles built on pickup truck frames, like the Toyota 4Runner) together with CUVs (smaller than SUVs and built on sedan frames, like the Honda CRV). In Figure 2(d) we display the number of products by vehicle style over time. In the early 1980's less than 25 SUVs were available to consumers (typically large truck-like vehicles) and after the year 2000 there were nearly 100 SUVs available in the market. Conversely, the count of available vehicles for other styles remained largely unchanged over the period of our sample.

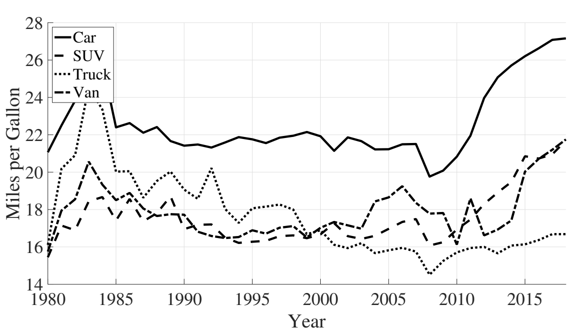
Figure 3: Physical Vehicle Characteristics, 1980-2018



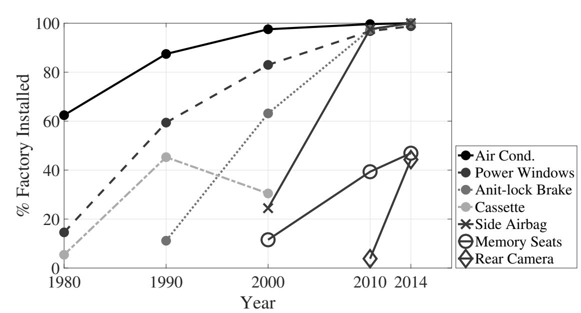
(a) Horsepower



(b) Size (length × width)



(c) Fuel Economy



(d) Additional Factory Installed Features

Notes: Panels (a)-(c) display average characteristics for available models in our sample. Panel (d) is the percent of each feature installed on total "cars" sold (i.e. not trucks, SUVs, or vans). Factory installed features were compiled from Wards Automotive Yearbooks from various years. For example, in 1980 61% of "cars" sold had air conditioning.

We display selected attributes over time in Figure 3. Average horsepower and car size (length by width) increased substantially from 1980 to 2018. Average horsepower more than doubled for cars and roughly tripled for trucks from 1980 to 2018, see Figure 3a. Cars became larger, SUVs and vans became smaller during the 1980s and then grew, and the average truck size grew substantially from 1980 to 2018. At the same time as horsepower and size increased, average fuel economy remained roughly constant, which largely reflects federal regulatory standards for fleet fuel economy, first enacted in the Energy Policy and Conservation Act of 1975.

Additionally, attributes not related to size and power changed substantially from 1980 to 2018. In Figure 3d, we show the percent of cars (i.e. not trucks, SUVs, or vans) sold with the following features, for years 1980, 1990, 2000, 2010, and 2014: air conditioning, power windows, anti-lock brakes, cassette player stereo system, side airbags, memory seats, and rear camera.[3] The percentage of cars with many of these features increased from 1980 to 2018, however both technology and trends in preferences affected the rate of adoption differently for different features. For example, air conditioning reached near universal adoption by 2000, but rear cameras are a recent addition. Safety features, like side airbags, were quickly adopted through the 1990s as federal safety regulations tightened. The cassette player, once a luxury feature, faded from cars as CDs and streaming services became popular, disappearing by 2010. In our demand model, many of these features will be subsumed into a quality residual which summarizes all characteristics not captured by readily available data like horsepower and vehicle size.

4 Model

Our framework is a differentiated product demand and oligopoly following Berry et al. (1995), which is standard in the industrial organization literature.

4.1 Consumers

Consumer i makes a discrete choice among the J_t options in the set $\mathscr{J}_t$ of car models available in year t and an outside "no-purchase" option (indexed 0), choosing the option that delivers the maximum conditional indirect utility.[4]

Utility is a linear index of a vector of vehicle attributes (x_{jt}), price (p_{jt}), an unobserved vehicle specific term (ξ_{jt}), and an idiosyncratic consumer-vehicle specific term (ϵ_{ijt}).

$$u_{ijt} = \beta_i \mathbf{x}_{jt} + \alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt} \tag{1}$$

The index i denotes an individual in a given year. We specify and estimate parametric distributions of taste parameters β_i and α_i across individuals that depend on time-varying demographics and allow for unobservable heterogeneity. In our baseline specification, the parameters are fixed

[3] These data were collected from Wards Automotive Yearbooks of the corresponding years.

[4] Our model focuses on consumers selection of a manufacturer product. In particular, we abstract away from financing, leasing, and dealership choice.

over time, but we relax this assumption in an alternative specification that we discuss in Section 5.5.

Utility of the no purchase option is $u_{i0t} = \gamma_t + \epsilon_{i0t}$, where γ_t reflects factors that change the utility of the no-purchase option from year to year, including business cycle fluctuations, urbanization, and durability of used automobiles. The average unobserved quality of new automobiles is also changing over time. We denote the mean utility of the choice set in year t relative to the base year as τ_t so that $\xi_{jt} = \tau_t + \tilde{\xi}_{jt}$ and $E[\tilde{\xi}_{jt}|\mathbf{z}_{jt}] = 0$, where $\mathbf{z}_{jt}$ is a vector of instruments including $\mathbf{x}_{jt}$, year dummies, and an instrument for price.

It is well known that discrete choice models only identify utility relative to the outside good. Therefore, without further restrictions, we would be unable to separately identify yearly average unobserved quality, τ_t, and the value of the outside option, γ_t. To address this issue, we follow Pakes et al. (1993b) and add the restriction that

$$\forall j \in \mathscr{C}_t : E[\xi_{jt} - \xi_{jt-1}] = E[(\tau_t - \tau_{t-1}) + (\tilde{\xi}_{jt} - \tilde{\xi}_{jt-1})] = 0 \quad (2)$$

where $\mathscr{C}_t$ is the set of vehicles offered in both year t and $t-1$ that have not been redesigned by the manufacturer. Consider a model j as being the same nameplate and design generation.[5] This restriction captures the fact that models within a model generation have substantively the same design from year to year, although it allows for idiosyncratic changes in features, marketing, or consumer taste. It separately identifies average quality of the choice set, τ_t from the average consumer valuation of the outside good, γ_t. Identification follows from a two step argument: First, following the usual logic of discrete choice models, $\tau_t - \gamma_t$ is identified. Second, given that $\tilde{\xi}_{jt}$ can be constructed from identified objects, the moment condition over continuing products (2) identifies τ_t (subject to the normalization that $\tau_0 = 0$). As this argument for identification is constructive, we will follow it closely when estimating the model below.

Separating average unobserved quality and the value of the outside option is important because we expect that unobserved product attributes change over time as in Figure 3d. It is important for us to incorporate this concept into consumer welfare. Second, the time effects capture aggregate economic conditions that influence the total sales of vehicles, but that are arguably not relevant for assessing the functioning of competition in the industry.

We model consumer heterogeneity by interacting household characteristics and unobserved preferences with car attributes. Our specifications for preferences are the following:

$$\alpha_i = \bar{\alpha} + \sum_h \alpha_h \mathrm{D}_{ih} \quad (3)$$

$$\beta_{ik} = \bar{\beta}_k + \sum_h \beta_{kh} \mathrm{D}_{ih} + \sigma_k \nu_{ik}, \quad (4)$$

[5] Vehicle models are periodically redesigned. Within a design generation and across years, models share the same styling and the same (or very similar) attributes. A typical design generation is between five and seven years.

where subscript k denotes the kth car characteristic (including a constant) and h indexes consumer demographics. Allowing for observed heterogeneity allows substitution patterns to differ by demographics. The distribution of D_{ih} is taken from the Current Population Survey. In practice, we do not interact every demographic with every car characteristic. See Table 4 for a complete listing of demographic - characteristic interactions and unobserved heterogeneity that we include in the model. Allowing for unobserved heterogeneity allows for more flexible substitution patterns. Unobserved taste for automobile characteristics, ν_{ik} are assumed to be independent draws from the standard normal distribution.[6]

Our baseline specification holds the parameters underlying the distributions of β_i and α_i fixed over time. That said, the distributions themselves can change over time because of changing demographics. For example, increasing income inequality will lead to increasing dispersion in the α distribution in our estimates. We also estimate a specification where we allow for time trends in some of the linear parameters β and α. As we report in Section 5.5, allowing for time trends does not substantially change the quantitative results. Therefore our baseline specification maintains stable-over-time parameters.

For a given year, market shares in the model are given by integrating over the distribution of consumers who vary in their demographics, unobserved tastes for characteristics, and idiosyncratic error terms,

$$s_{jt} = \int_i \frac{\exp(\beta_i x_j + \alpha_i p_j + \xi_j)}{\exp(\gamma_t) + \sum_{l \in \mathscr{J}_t} \exp(\beta_i x_l + \alpha_i p_l + \xi_l)} \, dF(i). \tag{5}$$

Shares conditional on consumer demographics can be computed by replacing the population distribution with the appropriate conditional distribution $F(i|D_{ih} \in \cdot)$. Moreover, second choice shares conditional on a given first choice vehicle can be computed similarly by integrating consumers' choice probabilities, when the first choice vehicle is removed, over the distribution of consumers, weighted by their probability of making that first choice.

4.2 Firms

On the supply side, we assume automobile manufacturers, indexed by m, play a static, full information, simultaneous move pricing game each year. Manufacturers choose the price for all vehicles for all of their brands, $\mathscr{J}_t^m$, with the objective of maximizing firm profit. Observed prices form a Nash equilibrium to the pricing game. We assume a constant marginal cost, c_{jt}, associated with producing a vehicle. The pricing first order condition for vehicle j is:

$$s_{jt} + \sum_{k \in \mathscr{J}_t^m} (p_{jt} - c_{jt}) \frac{\partial s_{jt}}{\partial p_{kt}} = 0 \tag{6}$$

These first order conditions will be used in conjunction with the estimated demand system to

[6] While we include a large set of random coefficients, we do not include unobserved heterogeneity on price to avoid estimating consumers with positive taste for price.

solve for marginal costs for each product. Marginal costs will then be used to compute price to cost ratios and for counterfactual analysis.

Our assumption of Nash-Bertrand pricing to maximize firms' profits rules out cartels or other changes in conduct over the time period.[7] If firms became more or less collusive, then the implied marginal costs inferred through assuming a static Nash equilibrium in prices would be misleading. We will consider alternative conduct assumptions for robustness and analyze alternative models of conduct in counterfactual analysis. However, we do not attempt to measure changes in conduct as in Bresnahan (1982), Lau (1982), or Duarte et al. (2020).

5 Estimation and Results

We estimate the model using GMM, closely following the procedures outlined by Petrin (2002) and Berry et al. (2004). Our estimation procedure is implemented in three steps. We briefly outline each step here and relagate a full description to Appendix A.

In the first step, we jointly estimate consumer heterogeneity and the mean consumer valuations. We compute the conditional demographic and second choice moments from the model and construct a GMM estimator matching these to their analogues in the consumer-level choice data. We employ micromoments from two sources: (1) demographic information linked to car purchases from MRI and CEX and (2) second choice information from the MaritzCX survey. An example of a moment for the first source is the difference between the observed and predicted average price for each quintile of the income distribution. For the second source, we match the correlations in car characteristics between the purchased and second choice cars.[8]

In the second step, we estimate $\bar{\alpha}$ and $\bar{\beta}$ and year fixed effects by regressing the estimated consumer mean valuations on product characteristics, prices, make dummies, and year dummies. Our assumption that $\mathbf{x}_{jt}$ and the real exchange rate are uncorrelated with product-level demand shocks provides the classic moment conditions for 2SLS. The year fixed effects absorb the structural parameters for annual variation in mean car quality, τ_t, and preference for outside good, γ_t.

In the third step we use the empirical analogue of the continuing product condition (2) to separately estimate τ_t and γ_t from the estimated year effects.

We compute standard errors using a bootstrap procedure. We re-sample the micro data, including the sampled households in the CEX and MRI surveys as well as the MaritzCX survey, and re-estimate the model following the same three step procedure. We account for the sampling variation in ξ_{jt} in the second step of the estimation procedure at the make level. In each bootstrap draw of the micro data, we employ a nested parametric bootstrap, clustering at the make level, of the second step estimation.

[7] We also rule out the effect that voluntary export restraints (VER) in the 1980s and corporate average fuel economy (CAFE) standards have on optimal pricing. See Goldberg (1995) and Berry et al. (1999b) for supply side models of VERs and Goldberg (1998) and Gillingham (2013) for models of CAFE standards. In both cases, the marginal costs we recover reflect the shadow costs of adhering to these restrictions.

[8] See Table 8 for a complete list of micromoments.

5.1 Parameter Estimates

Table 4 presents parameter estimates for our demand system. In addition to the estimates presented, we also include brand dummies, year dummies, and additional car characteristics that are not interacted with unobserved or observed heterogeneity. The estimates imply that higher income individuals are less price sensitive for the relevant range of incomes. Also, older households are estimated to be less price sensitive. Larger household have stronger preferences for vans and vehicle footprint. Rural households have a stronger preference for trucks.

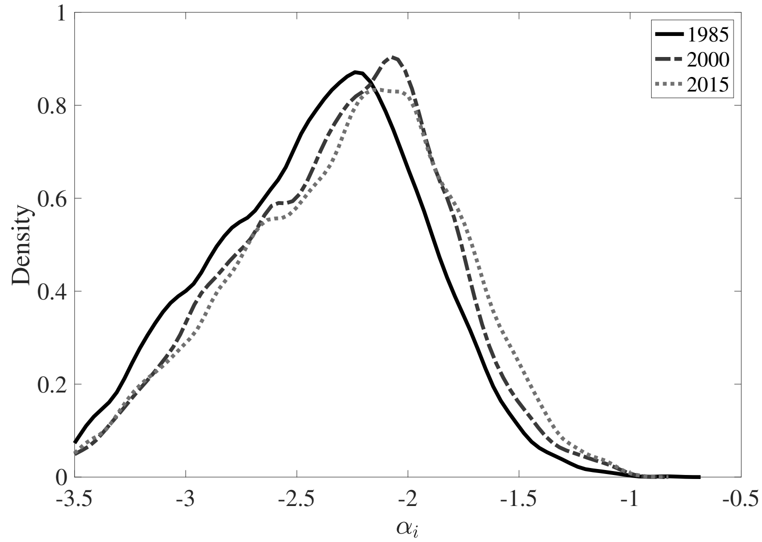
Table 4: Coefficient Estimates

			Demographic Interactions						
	$\bar{\beta}$	σ	Income	Inc.^{2}	Age	Rural	Fam. Size 2	FS 3-4	FS 5+
Price	-3.214	–	0.094	-0.464	2.068	–	–	–	–
	(1.157)		(0.009)	(0.112)	(0.104)				
Van	-7.588	5.348	–	–	–	–	1.668	3.563	5.653
	(0.52)	(0.103)					(0.144)	(0.151)	(0.202)
SUV	-0.063	3.646	–	–	–	–	–	–	–
	(0.332)	(0.064)							
Truck	-7.663	6.309	–	–	–	3.009	–	–	–
	(0.791)	(0.19)				(0.314)			
Footprint	0.911	1.884	–	–	–	–	0.483	0.463	0.645
	(0.31)	(0.043)					(0.045)	(0.048)	(0.06)
Horsepower	0.499	1.249	–	–	–	–	–	–	–
	(1.08)	(0.123)							
Miles/Gal.	-0.909	1.636	–	–	–	–	–	–	–
	(0.204)	(0.071)							
Luxury	–	2.627	–	–	–	–	–	–	–
		(0.028)							
Sport	–	2.62	–	–	–	–	–	–	–
		(0.043)							
Electric	-5.932	3.835	–	–	–	–	–	–	–
	(1.254)	(0.107)							
EuroBrand	–	1.923	–	–	–	–	–	–	–
		(0.03)							
USBrand	–	2.14	–	–	–	–	–	–	–
		(0.038)							
Constant	–	–	0.362	–	–	–	–	–	–
			(0.032)						
Height	-1.421								
	(0.367)								
Curbweight	0.303								
	(0.995)								
No. Trims	1.179								
	(0.154)								
Release Yr	-0.321								
	(0.151)								
Yrs Since Design	-0.325								
	(0.039)								

Notes: Brand and year dummies included. Standard errors account for correlation within make of realizations of ξ_{jt}. All continuous car characteristics are in logs and price is in 2015 \$10,000. Footprint is vehicle length times height in square inches. Dummies for the number of years since the vehicle has been redesigned, a dummy for a new design, and the number of available trims are also included in the regressions but not shown. Income is normalized to have zero mean and unit variance.

In general, we estimate large and economically meaningful coefficients representing unobserved heterogeneity, which rationalizes very strong substitution patterns observed in the second-choice

Figure 4: Distribution of Price Sensitivity



Note: Plot displays smoothed kernel regression of 10,000 draws from the estimated distribution of α_i, by year.

data. The largest random coefficients appear on vehicle style, suggesting consumers substitute mostly within vehicle style. Electric vehicles also have a large estimated random coefficient.

Although we fix model parameters over time in the baseline specification, the distribution of price sensitivity and other tastes does change due to the change in the distribution of consumers. For example, Figure 4 presents the distribution of consumers' price sensitivity, α_i, in 1985, 2000, and 2015. Over the data period there has been a shift in the mean distribution towards less price sensitivity, which is a reflection of higher incomes and an older population. This, together with changes in the product set, drives changes in the elasticity of demand. Table 5 summarizes the estimated own price elasticties based on the income of purchasers and how these change over time. In all years, higher income consumers tend to purchase more price-inelastic automobiles, consistent with the demographic interactions reported in Table 4. However, automobiles have become more elastic over time, despite rising incomes, due to changes in the product set. Our estimates of own-price elasticities for the earlier years in our sample are similar to BLP, Goldberg (1995), and Petrin (2002). Figure 4 shows how the distribution of price sensitivity α_i changes over time due to changes in demographic distributions.

Decomposition of Time Effects

The restriction in equation 2 decomposes the time effects into average improvements in unobservable car quality and relative movements in the utility of the outside good over time—potentially due to business cycle factors or changes in the utility of not purchasing a new car.

Figure 5 displays the results of this decomposition. We find that unobservable vehicle quality is steadily increasing roughly linearly by a cumulative total of about $20,000. The value of the outside option also generally increases over the time period with noticeable deviations from trend

Table 5: Own Price Elasticities by Income Quintile Over Time

	Income Quintile				
Year	1	2	3	4	5
1980	-5.90	-5.69	-5.92	-5.97	-5.69
2000	-8.19	-8.20	-8.12	-8.22	-8.30
2018	-9.08	-9.02	-8.66	-8.65	-8.66

Notes: This table reports the mean own price elasticity across products individuals conditional on income quintile of individuals in each reported year.

during the 1990-1991 and 2007-2009 recessions.

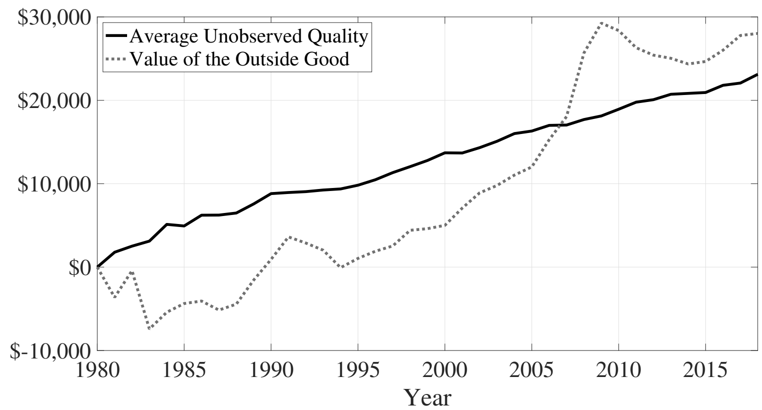
Our model points to a substantial improvement in the quality of automobiles over the sample period, equal to approximately the mean price of a new car in the early part of the sample period. The economic meaning of this increase is that a consumer faced with the choice between two automobiles of the same observable characteristics (e.g., size, horsepower, fuel economy) but with average unobserved quality (e.g., airbags, sound system, durability) of 1980 versus 2018 would place significantly higher value on the 2018 vehicle. To quantitatively assess the plausibility of the unobserved quality component, we manually collected data from the Kelly Blue Book website in 2021 for mint condition used automobiles produced every five years between 1992 and 2017. We then regressed the Kelly Blue Book private party transaction value against characteristics and dummy variables for the year of production. The year of production dummy variables should capture the average unobserved product differences across years of production. The full specification is presented in Appendix B.3. We find that the year of production dummies rise by $19,638.88 in between 1992 and 2017, which is about the same as the increase we estimate for the value of unobserved product improvements, suggesting the estimate is not implausibly large.

A number of narratives also support such large increases. Automobiles have become safer through features such improved air bag technology, body construction, rear view cameras, and blind spot sensors. According to the National Highway Traffic Safety Administration (NHTSA), fatalities not involving alcohol impairment per vehicle miles traveled (VMT) have decreased 40 percent between 1982 and 2019 from 1.27 per hundred million VMT to 0.74 per hundred million VMT.[9] Unobserved comfort improvements include power steering, durable interior materials, and electronic features such as Bluetooth audio systems and power or heated seats. Many of these features had not even been invented at the start of the sample.

Finally, car durability is likely an important aspect for both the increased quality of new cars and the value of the outside good (which includes driving used cars). We would expect increased car durability to increase the value of a car. Between 1980 and 2018, data from the NHTSA implies that the average time a consumer keeps a new car has risen from 3.9 to 5.9 years, consistent

[9]While this could also be due to safer driving behavior or safer road construction, the rise of distracted driving because of mobile handsets likely pushes in the opposite direction.

Figure 5: Quality and Aggregate Components of Time Effects



Notes: Average unobserved quality, τ_t, and value of outside good, γ_t, in dollars. See text for estimation details.

with increasing durability. This is part of the improvement in unobserved quality captured by our quality adjustment, τ_t, along with improvements in safety, comfort, and electronics. However, as cars become more durable, households will replace them less often, which has an effect of making the outside option appear more attractive. We expect this effect to be captured in the outside good part of the time effect, γ_t. The outside option series is also broader than durability, however. In addition to improvements in the attributes of used cars, the outside option can also be influenced by alternative transportation options such as public transport or ride sharing, or changes in the commuting needs of the population. It will also be affected by business cycle fluctuations which lead consumers to accelerate or postpone new car purchases.

5.2 Model Fit

We target correlations between the attributes of purchased cars and stated second choices for survey years 1991, 1999, 2005, and 2015. The first column of Table 6 presents the average correlation across years for each attribute we target. These correlations exhibit strong substitution patterns by observable characteristic. As seen in the second column of Table 6, our estimated model is able to match these moments well. We compare our fit to two models without unobserved heterogeneity. In column 3, we present the implied correlations from the logit model which assumes independence of irrelevant alternatives. More surprisingly, column 4 presents the implied correlations from a model with observed heterogeneity alone. That is, we allow tastes for automobile characteristics to vary with consumer demographics but drop the random coefficients from the model. Despite sometimes large differences in purchase behavior across demographic groups (see Appendix Table 8), which the estimated model is able to match, the implied second choice correlations are still small. Accounting for demographics alone is insufficient to generate substitution patterns implied by the second choice survey data.

Table 6: Attribute Correlation between First and Second Choice

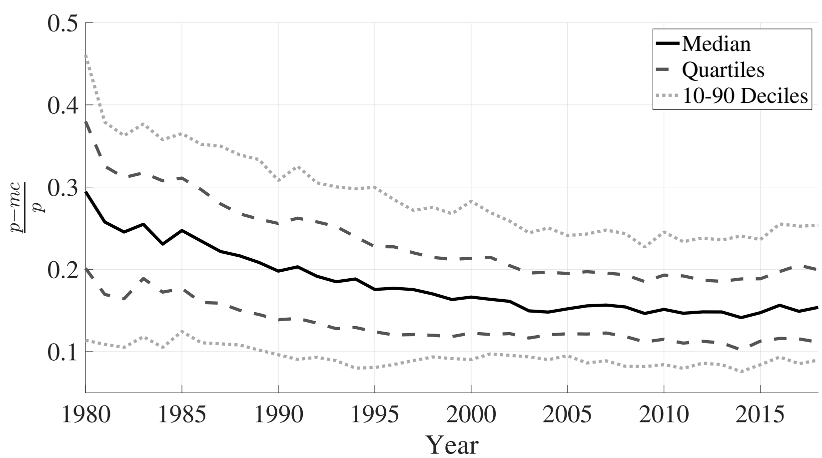
	Data	Model	Alternative Specifications: Logit	Alternative Specifications: Only Demographics
Van	0.71	0.71	-0.01	0.02
SUV	0.64	0.64	-0.01	0.03
Truck	0.84	0.80	-0.02	0.58
logSizeLW	0.71	0.69	-0.02	0.18
Horsepower	0.60	0.59	-0.01	0.07
MilesPerGallon	0.65	0.65	-0.01	0.08
Luxury	0.48	0.49	-0.01	0.02
Sport	0.28	0.28	-0.00	0.00
Electric	0.37	0.19	-0.00	0.00
EuroBrand	0.34	0.34	-0.00	0.01
USBrand	0.48	0.47	-0.01	0.02

Notes: Data from MaritzCX survey, 1991, 1999, 2005, 2015. The numbers are the average across these four years. "Model" column represents the predictions from the model presented in Table 4. The "Logit" column are contains model predictions from a simple logit demand specification. The "Only Demographics" column contains model predictions from a model with the same demographic interactions as our main specification, but without any unobserved heterogeneity. "Logit" and "Only Demographics" are estimated without moments on second choices.

5.3 Markup Estimates

In Figure 6 we display the median markups in terms of the Lerner index over time, as well as the 10th, 25th, 75th, and 90th percentiles. As anticipated by the increase in elasticities, median markups fell substantially between 1980 and 2018, from 0.248 in 1980 to 0.1373 in 2018. In 1980, the 10th percentile markup car had a markup of 0.099 and 0.081 in 2018. The 90th percentile was 0.388 in 1980 and 0.227 in 2018.

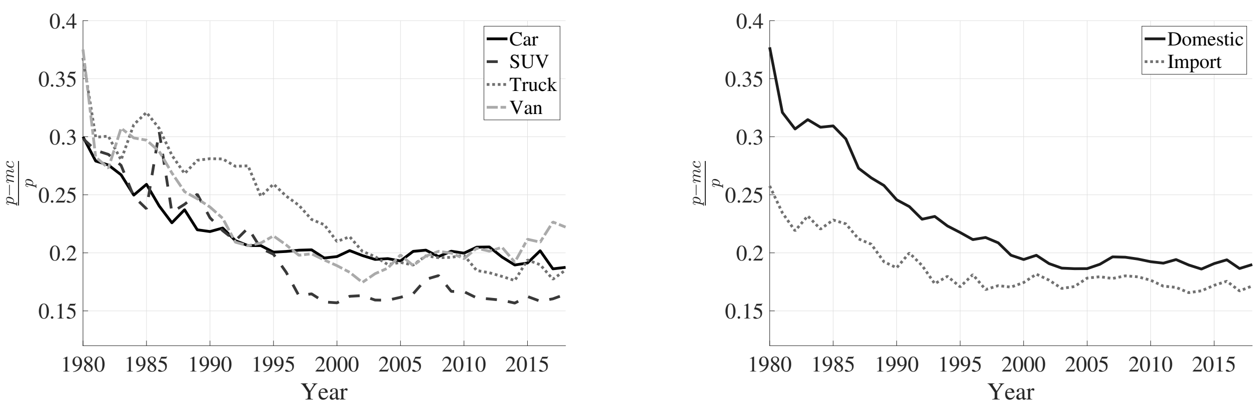
Figure 6: Markups Over Time



Notes: Estimated markups for the U.S. automobile industry, 1980-2018. Markups expressed as the Lerner index, price-cost margin over price, $\frac{p-mc}{p}$.

In Figure 7 we display median markups by vehicle style in panel (a) and by import status in panel (b). The decline in markups occurs across all vehicle styles and for both imported and domestically produced vehicles. Starting with panel (a), markups for trucks were higher than other vehicles in the beginning of our sample, but fell more steeply throughout the 1990's. This is likely due to two factors, a steeper increase in the quality and price of trucks and slightly greater competition as the popularity of foreign manufactured trucks increased. Markups for SUVs also experienced a sharp fall during the 1990s, likely due to the massive increase in competition in this segment, as the number of SUVs available nearly tripled during this time and our demand estimates imply strong within category substitution. Turning to panel (b) in Figure 7, overall, imported vehicles have lower markups than domestically produced vehicles, where our classification is based on country of production, not the headquarter country of the product. However, domestically produced vehicles experienced a much greater fall in markups over our sample period.

Figure 7: Markups over Time



(a) Markups by Vehicle Style (b) Markups by Import Status

Note: Median markups across all vehicles. Vehicle style defined in the text. "Domestic" are those cars produced in the U.S., regardless of brand headquarters.

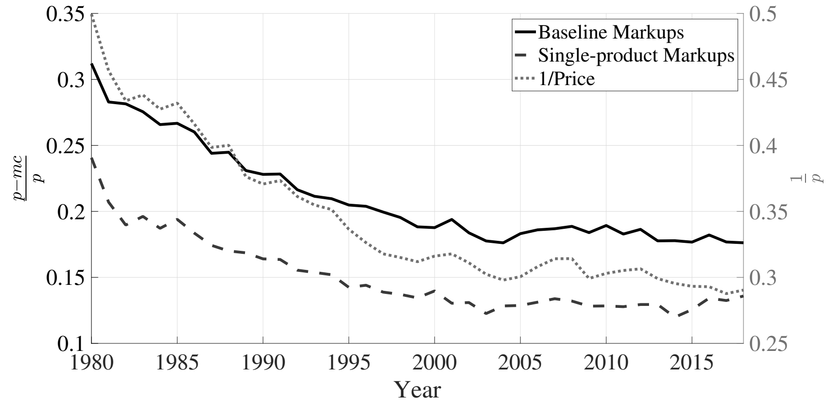
5.3.1 Explaining the Evolution of Markups

What drives the decline in markups? A key observation to understand the estimated change in markups is that the trend is similar if we infer markups assuming single product firms as seen in Figure 8 or assuming industry wide collusion in Figure 9. Therefore, decreases in concentration, although substantial, are not the primary driver in the estimated decrease of markups. In the single product firm case, the Lerner index is equal to the inverse elasticity of the product:

$$\frac{p-mc}{p} = \frac{1}{\text{elas}} = \frac{s}{p} \times \frac{1}{\frac{ds}{dp}} \tag{7}$$

At our demand estimates, the only component of the elasticity which changes substantially over time are prices. Mechanically, prices are increasing while shares and the derivative of share

Figure 8: Markups and Prices



Notes: Median markups for our baseline model and a model that assumes each product's price is set independently of all other products. "1/Price" is the average price each year.

with respect to price are roughly constant. This combination implies that markups decrease. To illustrate this, we also plot $1/p$ in Figure 8. It mirrors the trend in both single and multi-product markups.

The economic reason why prices are increasing without shares decreasing and without changes in the derivative of share with respect to price is because car quality is increasing. However, this highlights the fact that, markup trends over time are not conceptually attractive proxies for welfare when the product set is changing.[10] We will thus focus on the model's measures of welfare and surplus over time to assess industry performance in Section 6.

5.4 Robustness to Conduct Assumption

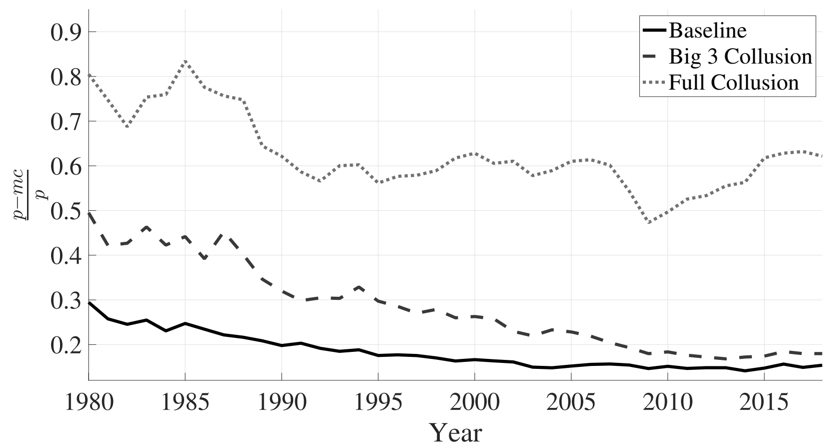
In this section, we compare markup estimates under alternative assumptions of conduct. To summarize the results, while there is great disparity in the level of markups, these alternatives all point towards declining markups over the sample period as in the base case of Nash-Bertrand pricing. In the first case, we assume the Big Three US auto manufacturers (G.M., Ford, and Chrysler) collude on prices for our entire sample.[11] Markups are much higher than our baseline case in the 1980s, but then become closer to our baseline case throughout time. This is consistent with the decline in the dominance of the Big-3 firms over time. Notably, markups at the end of the sample under the assumption that the Big-3 collude are *lower* than the Nash-Bertrand markups at the start of the sample. Therefore, under the assumption that the Big-3 were competing in 1980 and organized a

[10] For a simple example of when markups can be misleading, consider a logit monopolist with $u = \delta - \alpha p + \varepsilon$, whose market share is $s = \frac{\exp(\delta-\alpha p)}{1+\exp(\delta-\alpha p)}$. The pricing first order condition is $p = c + \frac{1}{\alpha(1-s)} = c + \frac{1}{\alpha}(1+\exp(\delta-\alpha p))$. Suppose the product improves in quality without changing its marginal cost. Totally differentiating the first order condition with respect to δ, we find $\frac{dp}{d\delta} = \frac{s}{\alpha} > 0$. Since marginal cost is constant, this implies markups rise. However, since $\frac{d(\delta-\alpha p)}{d\delta} = 1 - s > 0$ consumer surplus also increases.

[11] For Chrysler, we follow the ownership from Chrysler, to Daimler, to Cerebus private equity firm, then to Fiat and assume the owner of Chrysler colludes with all of the ultimate owner's brands. For example, then the Fiat brand is part of the "cartel" after 2012.

pricing cartel in response to import competition after 1980, we would still find a decline in markups between 1980 and 2018. In the second case, we consider markups that are implied if all of the firms colluded on prices. In this case, the level of markups are much higher, however there is still a decrease in markups over the time period.

Figure 9: Markups: Alternative Conduct Assumptions



Notes: Estimated median markups for Nash Bertrand pricing by parent companies ("Baseline"), the Big 3 U.S. automobile manufacturers colluding for every year in our sample ("Big 3 Collusion"), and joint price setting by every parent company in our sample ("Monopoly Collusion").

Figure 9 establishes that under a variety of constant conduct assumptions, markups decline over time. However, it is possible that a cartel could have formed during our sample period. We now ask how large such a cartel would need to be to have held markups constant over the period. To quantify this, we consider different size cartels in 2018 to measure how many cartel members it would take for a cartel in 2018 to achieve the baseline non-collusive level of markups found in 1980. Specifically, we form cartels with the largest-by-sales manufacturers, adding one manufacturer at a time. The results are in Table 7. One change in conduct from Nash-Bertrand that would produce estimated increases in markups would from 1980 would involve a cartel of the six largest parent companies. Overall, it seems that a price-fixing cartel on the scale needed to keep markups at their 1980 level would be unlikely to escape the notice of antitrust authorities.

5.5 Robustness to Trends in Preferences

Our estimates of markups and consumer surplus are functions of estimated own-price elasticities. In our main specification, we restrict the price parameter in the utility function to be constant across time. Elasticites change over time due to a changing product set and changing incomes. In this section, we consider whether fixing consumers' preferences over time may be restrictive. We estimate an alternative demand specifications where we allow for a linear time trend in the price parameter, as well as linear trends in preferences for vehicle type. To estimate this specification, we introduce an additional instrument: the interaction between our baseline instrument, lagged real exchange rate, and time.

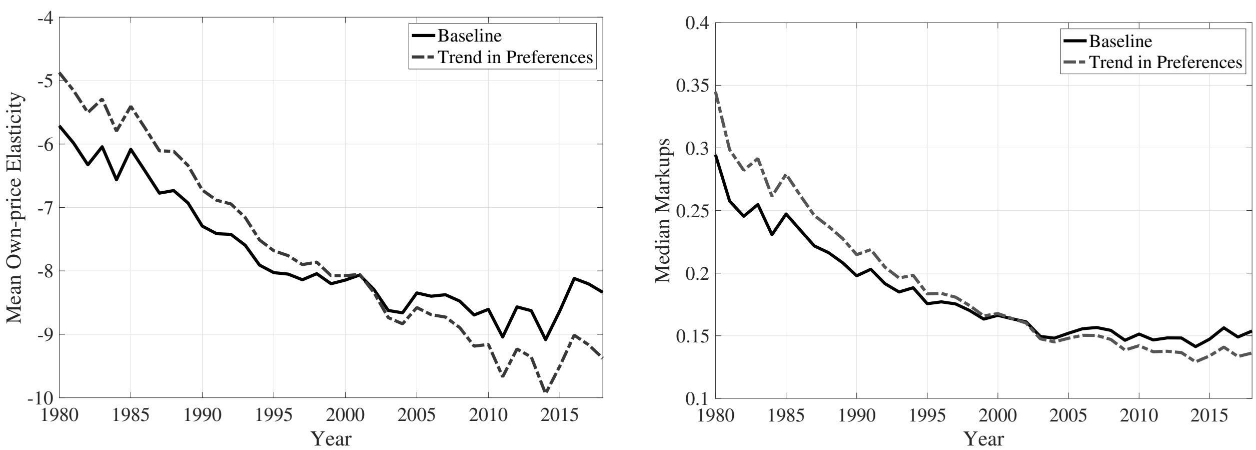
Table 7: Average Markups with Different Cartel Assumptions

	Average Markup
1980 Baseline	0.292
2018 Baseline	0.165
2018 Cartel Membership	
GM + Ford + Toyota	0.188
Top 3 + Fiat	0.227
Top 4 + Honda	0.251
Top 5 + Nissan	0.295

Notes: Computed average markups when we simulate collusion in 2018 for various manufacturer cartels. In 2018, Fiat is the parent company of Chrysler.

The results from this exercise are available in Appendix Table 9. We estimate a slight decreasing (but statistically insignificant) trend in the magnitude of price sensitivity, implying a slightly greater decrease in average markups. This is visible in Figure 10 which plots the yearly average own-price elasticities and yearly average share-weighted markups for our baseline specification and the alternative specification. Overall, allowing for a time trend in preferences leads to slightly less precise estimates, particularly early in the sample, but does not change the qualitative finding of decreasing markups.

Figure 10: Elasticities and Markups for Alternative Demand Specification



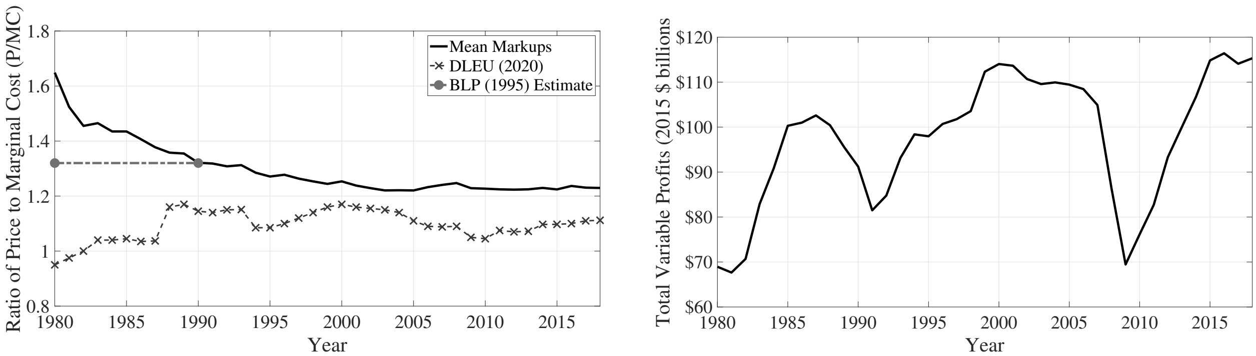
(a) Average Own-price Elasticities (b) Average Markups

Notes: Panel 10a displays the yearly average own-price elasticity of demand for two specifications: our baseline specification (solid line) and a specification where we allow the mean price coefficient and vehicle type coefficients to have a linear trend (dashed line). Panel 10b displays the average share-weighted markups over time for these two specifications. The shaded region represents the 95% confidence interval for mean markups.

5.6 Comparison to production-based approach

De Loecker et al. (2020) use financial and production data to estimate price to marginal cost ratios for a much of the US economy. They estimate a sizeable increase in the sales weighted average price to marginal cost ratio over the last several decades. Their approach uses a model of firm production and data on input expenditures and output revenue to estimate price over marginal cost ratios.[12] De Loecker et al. (2020) report estimates for the US auto industry time series of average price to marginal cost ratio which we compare to our measures in Figure 11a. Both the level and trends in the price to marginal cost ratio differs from the estimates we derive, though both series are relatively flat from 1995 on-wards.

Figure 11: Comparison to De Loecker et al. (2020)



(a) Price over Marginal Cost

(b) Total Variable Profits

Notes: Panel (a) displays share-weighted mean price over marginal cost in our estimates, the estimate for share-weighted mean price over marginal cost in the U.S. automobile industry from De Loecker et al. (2020), and the average estimate across 1971-1990 from Berry et al. (1995). Panel (b) displays our estimate of total variable profits, sales multiplied by margins, summed across all products.

There are several possible explanations for the difference in estimates displayed in Figure 11a. The demand and conduct approach employed in this paper could be flawed because the exclusion restriction for the instrumental variable we employ to estimate demand does not hold, or because the conduct assumption of static Nash pricing does not hold.[13] Likewise, production based estimates could be biased for a number of reasons: if the intermediate inputs observed in their data are not fully flexible, because of the assumption that firms in their data produce single products, or because the classification of accounting costs into costs of goods sold versus selling, general, and administrative costs does not accurately capture the distinction between marginal and average costs. Furthermore, the underlying data differ in that the Compustat based estimates in 11a do not capture some foreign based firms, and production based estimates using Census data would miss models assembled outside of the US and include commercial truck producers. Finally, the Compustat based estimates include additional revenue streams outside of automobile manufacturing such as any vertically integrated parts manufacturing or consumer financing operations. The DLEU series does share some patterns with our estimates of total variable profits over time including an increase in the 1980's, a dip and recovery in the 1990's, and a dip and recovery around the Great Recession.

[12] A number of papers including Traina (2018); Basu (2019); Raval (2020); Demirer (2020) examine the specific assumptions and data requirements used to construct these estimates.

[13] Although, as we note above, the downward trend in markups is robust to a variety of conduct assumptions.

While the discrepancy between our estimates of markups is interesting, a full analysis of the differences between these approaches is beyond the scope of our study. De Loecker and Scott (2016) examine production and demand approaches for beer and find both approaches find plausibly similar markup estimates. An important advantage of the demand side approach is that it provides a direct measures of consumer surplus which are not available without an estimated demand system and account for changing product quality. For the remainder of the paper, we will use our estimates to go beyond markups and analyze the welfare trends of the US Auto industry.

6 The Evolution of Welfare

What are the implications of our estimates for assessing the performance of the industry over time? It may seem natural to evaluate concentration and markups as proxies for welfare, and we documented that both concentration and markups have fallen. However, it is well known that the relationship between concentration and welfare is theoretically ambiguous (Demsetz, 1973). Above we show that the relationship between markups and welfare is ambiguous if the product set is changing and that our markup estimates are largely driven by the changing cost and quality of cars. This section directly examines welfare trends over time.

6.1 Consumer surplus, producer surplus, and deadweight loss over time.

We first define a consumer surplus measure appropriate for our context. Typically, studies use the compensating variation of the product set relative to only the outside good being available to consumers. While this approach is straightforward, it is sensitive to changes in the valuation of the outside good over time. For example, suppose consumers choose to delay buying cars during a macroeconomic downturn. Then in the down year the value of the outside good, γ_t will be high—as more consumers choose not to purchase. Similarly, suppose there is a significant improvement in public transit over time, this again is reflected in an increase in γ_t which will cause a decline in consumer surplus. It is easy to see that both of these cases will affect the standard consumer surplus measure, even when the quality of automobiles and their prices are held fixed. Since we are interested in how the industry has served consumers over time, rather than evolution in the outside good, we propose an alternative measure of consumer surplus that removes outside good effects.

To make things concrete, consider the compensating variation of a consumer being offered the inside product bundle in year t with the outside good valued at γ relative to receiving only the option to purchase this hypothetical outside good. Given our model assumptions, this is,

$$CS_t(\gamma) = \int_i \frac{1}{\alpha_i} \left[\log \left(\exp(\gamma) + \sum_{j \in \mathcal{J}_t} \exp(\beta_i \mathbf{x}_{jt} + \alpha_i p_{jt}^{\gamma} + \xi_{jt}) \right) - \gamma \right] dF_t(i). \tag{8}$$

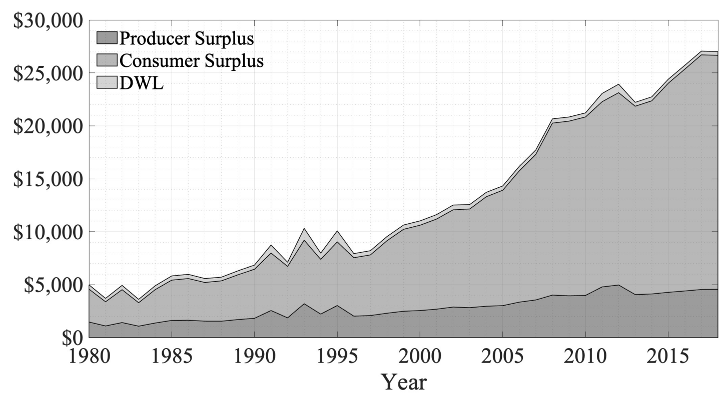
In this calculation, $\mathbf{p}_t^{\gamma}$ represents the equilibrium vector of prices when firms face an outside good valued at γ.

The traditional consumer surplus measure is simply $CS_t(\gamma_t)$—the compensating variation that would make consumers in year t indifferent between the product bundle they face and only the outside good from that bundle. However we can also examine how the inside product bundle in year t would have been valued against the the outside good in other years, enabling a direct comparison of product sets across years. Our preferred surplus measure removes the influence of changes in the outside good over time by averaging over the outside good across all years in the sample,

$$\widetilde{CS}_t = \frac{1}{T}\sum_{v=0}^{T} CS_t(\gamma_v).$$

We can compute producer surplus and deadweight loss measures analogously.

Figure 12: Consumer Surplus, Producer Surplus, and Deadweight Loss



Notes: Consumer surplus, producer surplus and deadweight loss. Consumer surplus in the compensating variation procedure detailed in the text. Deadweight loss is computed by netting consumer and producer surplus form efficient surplus, defined as the surplus available when prices equal marginal costs. Surplus measured in 2015 dollars.

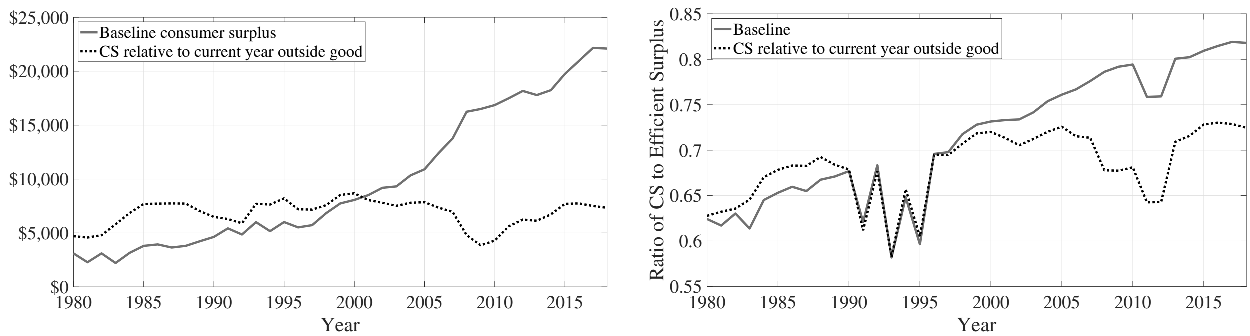
In Figure 12 we plot estimated consumer surplus ($\widetilde{CS}_t$), producer surplus, and deadweight loss over the sample period. These components sum to total efficient surplus, which we measure by computing surplus when prices equal marginal costs. Total surplus rises roughly $\$25,000$ per household, from around $\$5,000$ to nearly $\$30,000$. Overall, the market is very efficient, with deadweight loss representing a small portion of total efficient surplus. This finding is reminiscent of Bresnahan and Reiss (1991) who estimate that most of the increase in competition comes with the entry of the second and third firms on their sample of retailers in multiple industries. The U.S. automobile market typically features four or more parent companies producing each specific style of vehicle.[14]

Figure 13 contrasts our preferred welfare measure with the measure that fixes the value of the outside good at the current year's estimated value (e.g., $CS_t(\gamma_t)$). Figure 13a displays consumer surplus, in 2015 dollars. Under the alternative measure, consumer surplus is relatively flat over the

[14]This can be seen directly from the diversion implied by our demand model. A vehicle's highest diversion rivals are typically products offered by other parent companies. On average, of a vehicles 5 closest substitutes, 3.8 are produced by rival manufacturers, and 7.8 of top 10 substitutes are rivals.

period with marked troughs in the early 1980s, early 1990s, and 2009, corresponding to the three major economic downturns in our sample period. The difference between these panels is intuitive when we consider the significant changes in our estimates of the value of the outside good over time, as shown in Figure 5. Figure 13b plots the share of consumer surplus of total efficient surplus. We do this for our baseline measure of consumer surplus, as well as for a measure of consumer surplus where we compute the compensating variation to the current year's outside option. Consumers' share of available surplus is increasing from 1980 to 2018. For our baseline measure, consumers' share of surplus rising dramatically, from 0.63 to 0.79.

Figure 13: Consumer Surplus Comparison



(a) Consumer Surplus Comparison

(b) CS as a Share of Total Available Surplus

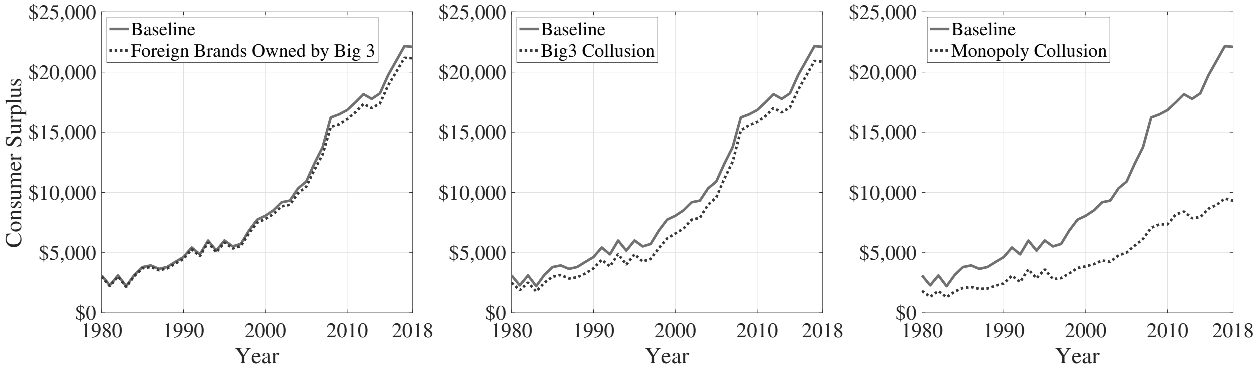
Notes: Panel (a) displays consumer surplus computed two ways: the baseline definition described in the text, and consumer surplus computed as the compensating variation to the current year outside good. Panel (b) displays the ratio of consumer surplus to total efficient surplus both way, where efficient surplus is computed as consumer surplus when prices equal estimated marginal costs of production, vehicle by vehicle.

6.2 Why does consumer surplus rise?

We now investigate the economic primitives driving the increase in consumer surplus over time. There are many plausible reasons for this increase. There has been a significant change in market structure; foreign brands now offer a larger proportion of products relative to the 1980s. The number of products available has also increased dramatically which benefits consumers due to increased variety and strong competition between models. Products have changed in terms of characteristics in numerous ways: Today, there are many SUVs available, whereas they were a negligible part of the market in 1980. Automobiles are larger, more powerful, more efficient and offer greater comfort and reliability than in the past. Finally, production has become more efficient. We propose a series of counterfactuals where we isolate these industry trends and recompute equilibrium outcomes to determine which are the main drivers of consumer surplus growth.

Mechanism 1: Increased competitive pressure form foreign brands. It is possible that the increase in foreign brands competing in the US led to downward pressure on prices that benefited

Figure 14: Consumer Welfare, Alternative Product Ownership



Notes: Vertical axis represents consumer surplus in 2015 dollars. In the first panel, we simulate the market equilibrium if all vehicles produced by foreign brands were owned by the Big 3 U.S. car manufacturers. In the second panel we simulate market the equilibrium if the Big 3 jointly set prices. In the third panel we simulate market equilibrium if all firms jointly set prices.

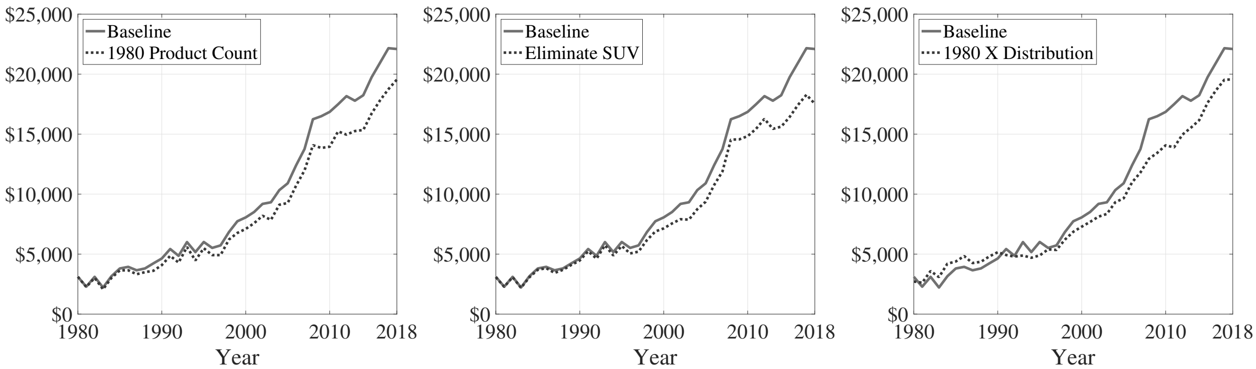
consumers.[15] To understand this mechanism, we simulate an alternative scenario where we assume all vehicles sold by foreign brands in our data are instead owned by the Big 3 US car manufacturers (General Motors, Ford, and Chrysler), so that these manufacturers internalize the competitive pressure of the increase in foreign-owned products over our time period. To implement this, we randomly assign ownership of foreign brand vehicles to one of the Big 3 firms. We do this ten times and take an average of the outcomes across the random assignments. Chrysler itself experiences ownership changes, so we track the ultimate owner of the Chrysler brand and treat that company as a Big 3 firm.

The results, in terms of consumer surplus, are presented in the left panel of Figure 14. Throughout this section, the soild line in figures corresponds to our baseline consumer surplus, and the dashed line corresponds to a counterfactual. Our estimates indicate that, had foreign brands been owned by domestic firms, consumer surplus would still have increased substantially. We conclude that the competitive pricing pressure from foreign brands was not a primary driver of the rise in consumer surplus. Again, this is consistent with competition constraining market power with only a few competitors within clusters of similar products.

We benchmark the result against two alternatives to emphasize this point. In the middle panel, we plot a counterfactual where we assume the Big 3 coordinate pricing for the entire period without owning imports, and in the right panel we show a case where all firms enter into a cartel to maximize joint profits. Only in the the full cartel case is the gain in consumer surplus dampened substantially. In other words, by changing the ownership structure, the model is able to deliver outcomes where consumer surplus is greatly reduced, but the ownership configuration which eliminates foreign-brand competition does not achieve this.

[15]There is a distinction between foreign brands and imports. Foreign brands are brands owned by parent companies traditionally headquartered outside of the U.S. Many foreign brands assemble vehicles in the U.S. (not imports) and many U.S. brands assemble vehicles in other countries and import to the U.S.

Figure 15: Consumer Welfare Product Set Counterfactuals



Notes: Vertical axis represents consumer surplus in 2015 dollars. In the first panel, we simulate the market equilibrium if we eliminate (randomly) products in every year so that in each year there are 165 products. In the second panel we eliminate all SUVs from our sample and simulate market the equilibrium. In the third panel we make the distribution of physical car attributes in the demand specification (horsepower, MPG, curbweight, footprint, and height) the same as the 1980 distribution and simulate market equilibrium.

Mechanism 2: Product proliferation. Another potential reason for the increase in consumer surplus is the increase in the number of available products. Consumer welfare increases with the number of products for two reasons. First, consumers like variety. Second, additional products in the choice set crowds the characteristics space and adds to competitive pressure.

To quantify this mechanism, we simulate an alternate market where we restrict the number of active products to be at the 1980 level, 165 available products.[16] The results are presented in the left panel of Figure 15. There is not much gap between the counterfactual consumer surplus and the estimated baseline path of consumer surplus. This is particularly striking considering that there were over 314 products in 2018, so the choice set was reduced by more than half. This suggests that product proliferation was not a significant driver of the consumer surplus increase.

Mechanism 3: Changing product attributes. We now turn to changes in product characteristics. The first major development we consider is the rise in the the number of SUV's available to consumers, as we documented in Figure 2d. SUVs represent a new and popular segment of the automobile market that was essentially unavailable in 1980. We estimate significant heterogeneity in taste for SUVs, which suggests the possibility of the introduction of SUV to generate significant consumer surplus. In the center panel of Figure 15, we display a counterfactual where we eliminate all SUVs from the choice set. As expected, this has a larger effect in the later years of the sample, when SUVs are more numerous. However, while consumer surplus is lower than baseline, the difference is modest and only explains a small portion of the rise in consumer surplus between 1980 and 2018.

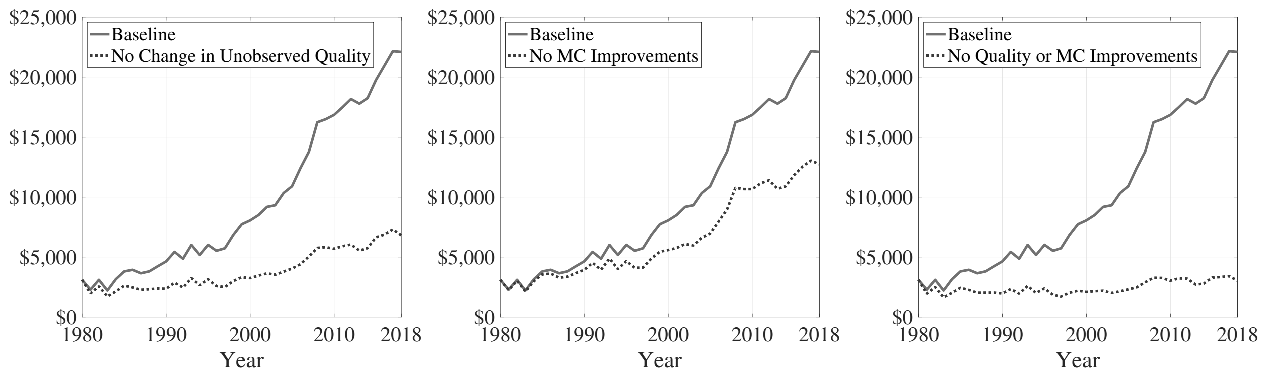
Another notable trend in the industry has been the general growth in car characteristics such as size and horsepower, as we documented in Figure 3. To see how these improvements affected

[16] In practice, we randomly select 165 products to be available each year. We do this procedure ten times and take an average of the outcome.

consumer surplus, we scale the distribution of horsepower, MPG, and footprint for each year in the sample to match the mean and variance of these characteristics in the 1980 choice set. This exercise affects consumer utility holding marginal cost fixed for all products. The results are displayed in the right panel of Figure 15. Consumers do prefer the choice set available to them at the end of the period, but this channel as well can not explain much of the increase in consumer surplus.

In addition to improvements in observable characteristics, we documented a steady rise in unobservable quality (Figure 5). In the left panel of Figure 16, we simulate a counterfactual where the unobservable mean vehicle quality is fixed at 1980 levels. Specifically, the rise in ξ is captured by the quality adjustment term τ in (2). We set $\tau_t = 0 \ \forall t$. In this case, the counterfactual delivers substantially lower increases in consumer surplus between 1980 and 2018. This comparison suggests that a large portion of the increased surplus enjoyed by consumers is due to improvements to vehicles that are outside our observed set of characteristics, such as safety features like rear view cameras, reliability improvements, and improved electronics like Bluetooth audio systems.

Figure 16: Consumer Welfare Unobservable Quality and Marginal Cost Counterfactuals



Notes: Vertical axis represents consumer surplus in 2015 dollars. In the first panel, we simulate the market equilibrium if we eliminate the adjustment to unobserved product quality, τ from equation X. In the second panel we eliminate all trend in marginal cost efficiency improvements and simulate market the equilibrium. In the third panel we eliminate τ and the trend in marginal costs efficiency.

Mechanism 4: Decreasing costs. As we report in Appendix B.2, our results indicate that marginal costs of producing a car with fixed characteristics has experienced a steady decline over the sample period. To investigate the welfare implications of these technological improvements, the middle panel of Figure 16 eliminates the downward trend in marginal costs. Since the trend is negative, this removes the benefits from decreasing marginal costs over time. We find that welfare increases by about half as much as in the baseline. Thus falling technological progress in reducing marginal costs is also a significant driver of the measured increase in consumer surplus.

Finally, in the right panel of Figure 16, we combine the left and middle panel counterfactuals and simulate a world where neither the unobservable product quality increases nor do marginal costs fall. This combination almost entirely eliminates the measured increase in consumer surplus.

7 Conclusion

Antitrust policy has come under scrutiny in the US in recent years. Critics argue that weak antitrust enforcement from the 1980's onward has led to an increasingly tight grip of large firms over product markets to the detriment of consumers. In this paper, we focus on the new automobile market over the last forty years. Employing a supply and demand industry oligopoly model with detailed microdata, we find that concentration has decreased, markups have decreased (in contrast to findings in studies estimating markups using accounting data), and consumer welfare has increased. The fraction of efficient surplus accruing to consumers has also increased.

We attribute the increase in consumer surplus primarily to increasing product quality and decreasing marginal costs. Specifically, we find that unobservable attributes- those that are not measured by specifications such as size, horsepower, and fuel efficiency- have increased significantly. These attributes include characteristics like safety, reliability, comfort, and improved electronics. We find that competition was healthy enough that benefits from these improvements mostly accrued mostly to consumers. However, our simulations indicate that had competition been significantly weaker, for example under a monopoly, then consumer benefits would have been offset through higher prices.

Our analysis makes a number of important assumptions. We assume a model of firm conduct to infer marginal costs. Testing different models of firm conduct to detect changes over time would be a useful direction for future research. Moreover, we do not analyze adjacent markets such as the market for financing, parts suppliers, labor, or retail dealerships. Profits and firm behavior in these markets are linked and could be offsetting the changes we measure here. We largely abstract away from the used car market except as it appears in a time-varying outside option for consumers in our model. More detailed modelling of the joint dynamics of new and used cars could lead to more precise measurements of consumer welfare.

Most importantly, to speak to the broader question of the performance of antitrust and industry regulation, more long term studies of specific industries are necessary. While broad based studies using accounting or production data are important and attractive due to their feasibility, specific industry studies are useful to validate measurements. Furthermore, as proxies for welfare such as concentration or markups can be misleading in an environment where products are improving over time, specific industry studies often lend themselves to direct welfare calculations thereby avoiding the use of proxy measurements.

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A Demand Estimation Procedure

A.1 Unobserved Heterogeneity and Mean Valuation

Following Berry et al. (1995) we can decompose a consumer utility net of taste for the outside good into a vertical component δ_{jt} and horizontal components,[17]

$$u_{ijt} - \gamma_t = \delta_{jt} + \mu_{ijt}(\theta) + \epsilon_{ijt}.$$

Where the vertical component is

$$\delta_{jt} = \bar{\beta}\mathbf{x}_{jt} + \bar{\alpha}p_{jt} + \xi_{jt} - \gamma_t \tag{9}$$

and the heterogeneity term is

$$\mu_{ijt}(\theta) = \sum_k \sum_h \beta_{kh} x_{jt}^k D_{ih} + \sum_h \alpha_h p_j D_{ih} + \sum_k \sigma_k x_{jt}^k \nu_{ik}, \tag{10}$$

where x_{jt}^k is the kth element of $\mathbf{x}_{jt}$ and we collect the heterogeneity parameters into the vector $\theta = (\{\beta_{kh}\}, \{\alpha_h\}, \sigma)$.

Our goal in this step is to estimate (θ, δ). For any consumer i, the conditional choice probability as a function of parameters is

$$\mathcal{s}_{ij}(\theta, \delta) = \frac{\exp\left(\delta_{jt} + \mu_{ijt}(\theta)\right)}{1 + \sum_{k \in J_t} \exp\left(\delta_{kt} + \mu_{ikt}(\theta)\right)}. \tag{11}$$

Integrating these choice probabilities over the distribution of consumers gives us the market shares. Since there is a one-to-one mapping between δ and market shares, we can solve for mean valuations as a function of θ by matching model predicted shares to the market share data,

$$s_{jt} = \int \mathcal{s}_{ij}(\theta, \delta(\theta)) dF_t(i).$$

We can now construct the moments for our estimator of θ. Let $\mathcal{s}_{ij}(\theta) = \mathcal{s}_{ij}(\theta, \delta(\theta))$. For readability, we drop t from the notation from the rest of this section and let y_i be the observed purchase of consumer i

Our first set of moments rely on micro-data where we observe consumers' automobile choice as well as their demographic characteristics, so we observe a random sample $\{y_i, \mathbf{D}_i\}$. We use this information to match product characteristics conditional on consumer demographics. Specifically,

[17] In this stage of estimation, it is convenient to re-normalize utility to be net of the outside good in year t, so that γ_t is a term in δ_{jt}. We will show how to estimate γ_t below.

we construct moments of the form[18]

$$\mathbf{g}_1(\theta) = E[\widehat{\mathbf{x}_{y_i}|i \in \mathscr{H}}] - \int \sum_j \mathbf{x}_j s_{ij}(\theta)\ dF(i|i \in \mathscr{H}), \tag{12}$$

where $\mathscr{H}$ describes a set of consumers identifiable based on demographics and $E[\widehat{\mathbf{x}_{(y_i)}|i \in \mathscr{H}}]$ is an estimate from the micro-data. In practice, we match differences and ratios of $\mathbf{g}_1(\theta)$ across alternative demographic sets. Table 8 lists the demographic moments we target and the associated model fit.

Our second set of moments relies on micro-data for which we observe the consumers first and second choices of products. That is, the data is a random sample $\{y_i, z_i\}$, where z_i is the stated second choice of consumer i. Conditional on purchasing an automobile, our model predicts the first and second choices of consumer i,[19]

$$s_{i(j,k)}(\theta) = \frac{\exp\left(\delta_j(\theta) + \mu_{ij}(\theta)\right)}{\sum_{\ell \in J} \exp\left(\delta_\ell + \mu_{i\ell}(\theta)\right)} \cdot \frac{\exp\left(\delta_k(\theta) + \mu_{ik}(\theta)\right)}{\sum_{\ell \in J \setminus j} \exp\left(\delta_\ell + \mu_{i\ell}(\theta)\right)}. \tag{13}$$

We construct moments based on the correlation of product characteristics of first and second choices,

$$\mathbf{g}_2(\theta) = E[\widehat{\mathbf{x}_{y_i} \circ \mathbf{x}_{z_i}}] - \int \sum_{j,k} (\mathbf{x}_j \circ \mathbf{x}_k) s_{i(j,k)}(\theta) dF(i) \tag{14}$$

where $\circ$ denotes element-wise multiplication and $E[\widehat{\mathbf{x}_{y_i} \circ \mathbf{x}_{z_i}}]$ is an estimate based on the micro-data. Table 6 displays the second choice correlations we target and the model fit.

We stack these two sets of moments and estimate θ via simulated GMM. We use a weight matrix based on the inverse variance matrix of the data moments. Simulation over the distribution of consumers follows Pakes and Pollard (1989). Given $\hat{\theta}$, our estimate of mean valuations is $\hat{\delta} = \delta(\hat{\theta})$.

A.2 Mean Taste for Characteristics

With the estimates of mean valuations from the previous step, we can now estimate mean tastes for product characteristics. We use the following regression equation,

$$\delta_{jt} = \bar{\beta}\mathbf{x}_{jt} + \bar{\alpha} p_{jt} + \iota_t + \tilde{\xi}_{jt}, \tag{15}$$

where $\iota_t = \tau_t - \gamma_t$ absorbs the effect of the average utility of the outside good and the average car quality in year t. We use our first stage estimate $\hat{\delta}$ as a proxy for δ and employ a simple (IV) regression where the real exchange rate is our instrument for price.

[18] In practice, we condition this moment on purchasing an automobile, since the outside good does not have characteristics. An exception to this is that we do include one moment based on purchase probabilities in order to estimate a demographic coefficient on the constant.

[19] Our second choice data does not include information on outside good selection, so we again condition out the no purchase option when constructing second choice moments.

Table 8: Moments and Model Fit

	MRI			CEX		
	Data	Model	Only Demos	Data	Model	Only Demos
x = Price (\$10k)						
$\mathbb{E}[x\|Income\,Q_5] - \mathbb{E}[x\|Income\,Q_1]$	0.60	0.40	0.42	0.22	0.38	0.36
$\mathbb{E}[x\|Income\,Q_4] - \mathbb{E}[x\|Income\,Q_1]$	0.36	0.27	0.27	0.02	0.23	0.21
$\mathbb{E}[x\|Income\,Q_3] - \mathbb{E}[x\|Income\,Q_1]$	0.19	0.15	0.16	-0.08	0.13	0.11
$\mathbb{E}[x\|Income\,Q_2] - \mathbb{E}[x\|Income\,Q_1]$	0.07	0.08	0.08	-0.15	0.07	0.07
$\mathbb{E}[x\|Age > 60] - E[x\|Age < 30]$	0.26	0.34	0.35	0.52	0.37	0.32
$\mathbb{E}[x\|Age50 - 60] - E[x\|Age < 30]$	0.24	0.29	0.32	0.39	0.34	0.33
$\mathbb{E}[x\|Age40 - 50] - E[x\|Age < 30]$	0.27	0.24	0.29	0.33	0.29	0.29
$\mathbb{E}[x\|Age30 - 40] - E[x\|Age < 30]$	0.27	0.14	0.14	0.27	0.15	0.14
x = Van						
$\mathbb{E}[x\|Family = 2] - \mathbb{E}[x\|Family = 1]$	0.02	0.02	0.02	0.03	0.02	0.02
$\mathbb{E}[x\|Family = 3/4] - \mathbb{E}[x\|Family = 1]$	0.06	0.06	0.06	0.06	0.06	0.06
$\mathbb{E}[x\|Family = 5+] - \mathbb{E}[x\|Family = 1]$	0.12	0.12	0.12	0.13	0.13	0.13
x = Car Size (length X width, log inches)						
$\mathbb{E}[x\|Family = 2] - \mathbb{E}[x\|Family = 1]$	0.03	0.03	0.03	0.04	0.03	0.03
$\mathbb{E}[x\|Family = 3/4] - \mathbb{E}[x\|Family = 1]$	0.03	0.02	0.02	0.02	0.02	0.02
$\mathbb{E}[x\|Family = 5+] - \mathbb{E}[x\|Family = 1]$	0.04	0.04	0.04	0.03	0.03	0.03
x = Truck						
$\mathbb{E}[x\|Rural] - \mathbb{E}[x\|NotRural]$	–	–	–	-0.10	-0.10	-0.10
x = Purchase Probability						
$\mathbb{E}[x\|Income\,Q_2]\,/\,\mathbb{E}[x\|Income\,Q_1]$	2.27	1.66	1.70	–	–	–
$\mathbb{E}[x\|Income\,Q_3]\,/\,\mathbb{E}[x\|Income\,Q_1]$	3.64	2.71	2.85	–	–	–
$\mathbb{E}[x\|Income\,Q_4]\,/\,\mathbb{E}[x\|Income\,Q_1]$	5.47	5.08	5.24	–	–	–
$\mathbb{E}[x\|Income\,Q_5]\,/\,\mathbb{E}[x\|Income\,Q_1]$	7.81	9.24	9.09	–	–	–

Notes: Moments from the consumer samples that we target in estimation, along with the analog from our model at the estimated parameters. For the demographic moments, our data comes from two surveys, the Consumer Expenditure Survey (CEX) covering years 1980-2005 and MRI covering years 1992-2018. The "Only Demos" column correspond to a specification where we include all of the demographic interactions but none of the random coefficients.

A.3 Mean Quality over Time

Our final step estimates τ and γ separately using the continuing product condition (2). The empirical analogue of this condition can be rewritten as an estimator of τ_t using the residuals from our second step,

$$\hat{\tau}_t = \hat{\tau}_{t-1} + \sum_{j \in \mathscr{C}_t} (\hat{\hat{\xi}}_{jt-1} - \hat{\hat{\xi}}_{jt}), \tag{16}$$

with τ_0 normalized to 0. Finally, we can estimate $\hat{\gamma}_t = \hat{\iota}_t - \hat{\tau}_t$.

B Additional Results and Analysis

B.1 Alternate Specification with Trends in Preferences

We estimate an alternative specification where we allow the linear price coefficient, and the preferences for SUV, truck, and van, to have a linear trend between 1980 and 2018. The results are presented in Table 9.

Table 9: Coefficient Estimates from Alternate Specification

	$\bar{\beta}$	s.e.
Price	-2.846	(0.782)
Price Trend	-0.017	(0.030)
Height	-1.285	(0.308)
Footprint	0.787	(0.290)
Horsepower	0.600	(1.141)
MPG	-0.925	(0.219)
Curbweight	0.336	(0.817)
No. Trims	1.188	(0.111)
Release year	-0.363	(0.158)
SUV	-2.870	(0.613)
Truck	-6.963	(0.832)
Van	-6.162	(0.667)
Electric	-5.736	(1.412)
Yrs Since Design	-0.335	(0.036)
SUV Trend	0.098	(0.018)
Truck Trend	-0.049	(0.038)
Van Trend	-0.088	(0.030)

Notes: Brand and year dummies included. Standard errors account for correlation within make of realizations of ξ_{jt}. All continuous car characteristics are in logs and price is in 2015 $10,000. Footprint is vehicle length times height in square inches. Dummies for the number of years since the vehicle has been redesigned, a dummy for a new design, and the number of available trims are also included in the regressions but not shown. Income is normalized to have zero mean and unit variance.

B.2 Determinants of Marginal Cost

In the counterfactual exercises of Mechanism 4, we consider scenarios that alter the marginal cost of products. To do so, we estimate a parsimonious model of the determinants of marginal cost, relating them to observable characteristics, the real exchange rate, and a linear time trend to capture technological innovation.

$$log(c_{jt}) = \mu \mathbf{x}_{jt} + \psi \cdot \mathrm{RXR}_{jt} + \rho \cdot t + \omega_{jt}, \tag{17}$$

Where $\mathbf{x}_{jt}$ is the characteristic set used in utility and RXR_{jt} is the real exchange rate (our cost instrument).[20] The coefficient estimates for this estimation are provided in Table 10.

For the first exercise in counterfactual Mechanism 4, which produces the middle panel in Figure 16, we compute counterfactual marginal costs by eliminating the technological improvements represented by the time trend (i.e., setting $\rho = 0$) while holding everything else fixed (including the residuals). We then solve for a new price equilibrium and compute the resulting consumer surplus. For the final counterfactual exercise in mechanism 4, we again eliminate the time trend in marginal cost, but this time also remove the estimated improvement in mean product quality from utility by setting $\tau_t = 0$ for all years.

[20] We have also experimented with including unobserved quality ξ_{jt} in the specification for marginal cost. While this produces qualitatively similar results for the counterfactuals, we opted to omit ξ from our baseline specification since it incorporates a mix of technological improvements many of which (such as inventing anti-lock breaks in 1980) are likely not directly attributable to marginal costs.

Table 10: Marginal Cost Function Estimates

Attribute	**Coefficient**	**S.E.**
Trend	-0.014	(0.002)
RXR	0.203	(0.029)
Height	-0.129	(0.018)
Footprint	-0.050	(0.017)
HP	0.255	(0.022)
MPG	0.022	(0.012)
Curbweight	0.321	(0.031)
No. Trims	-0.029	(0.006)
Release Year	-0.006	(0.013)
SUV	0.016	(0.026)
Truck	-0.118	(0.036)
Van	0.055	(0.029)
EV	0.304	(0.060)
Design Years	0.002	(0.004)
Years Since Redesign Effect	✓	
Brand Effect	✓	

Notes: Dependent variable is log marginal costs recovered from the first-order conditions. All attributes are in logs except RXR and $Trend$. Standard errors are clustered by brand.

B.3 Used Car Analysis

We manually collected data from the Kelly Blue Book website in December 2021 for mint condition, the best possible options, which KBB reflects 1-2% of the vehicles they evaluate, used automobiles with a total of 500 miles driven produced every five years between 1992 and 2017. Our query asked for the private party transaction value of the top five vehicles in each of the years for each of cars, SUV's, vans, and trucks. We then regressed the midpoint of Kelly Blue Book private party transaction value range against characteristics and dummy variables for the year of production. The year of production dummy variables should capture the unobserved product differences across years of production.

Table 11: **KBB Price Regression**

	Coefficient	S.E.
Height	26058.27	(5244.96)
Footprint	12470.29	(6862.72)
Horsepower	600.47	(2407.91)
MPG	-258.53	(4450.29)
Weight	-9710.17	(5279.84)
No. Trims	-2.65	(11.90)
Years Since Redesign	-99.44	(100.48)
Sport	-	-
Electric	-	-
Truck	-1809.78	(1403.22)
SUV	421.12	(1223.43)
Van	-1124.60	(1101.78)
Year 1997	-586.04	(951.43)
Year 2002	395.62	(1251.81)
Year 2007	3424.69	(1506.16)
Year 2012	10224.18	(1485.64)
Year 2017	19638.88	(1956.91)

Notes: Unit of observations: year make-model, from 1980 to 2018. Number of observations: 72. Specification include make fixed effects. Car characteristics in logs.