The Evolution of Market Power in the US Auto Industry*

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Abstract

We construct measures of industry performance and welfare in the U.S. car and light truck market from 1980-2018. We estimate a differentiated products demand model for this market 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 under the conduct assumption of Nash-Bertrand pricing. We relate trends in consumer welfare and markups to industry trends in market structure and the composition of products, like the rise of import competition, the proliferation of SUV's, and changes in vehicle characteristics. We find that although prices rose over time, concentration and market power decreased substantially. Consumer welfare increased over time due to improving product quality and falling marginal costs. The fraction of total surplus accruing to consumers also increased.

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

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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 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 0.311 in 1980 to 0.196 by 2018. However, the industry model indicates that 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. To quantify changes in welfare over time, we utilize a decomposition from Pakes et al. (1993a) to develop a measure of consumer surplus. 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 total surplus going to consumers went from 0.63 in 1980 to 0.83 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 falling marginal costs. 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 characteristics 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). 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 fall in marginal costs lead to a reduction in most 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. 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. Other papers which analyze outcomes in other industries over long time periods include Berndt and Rappaport (2001), Berry and Jia (2010), Borenstein (2011), and Brand (2020).

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.

In Table 1 we display summary statistics for our sample of vehicles at the make-model-year level, so 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

[1] We use Wards' vehicle style designations to create our own vehicle designations. We aggregate CUV (*crossover*

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.

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.

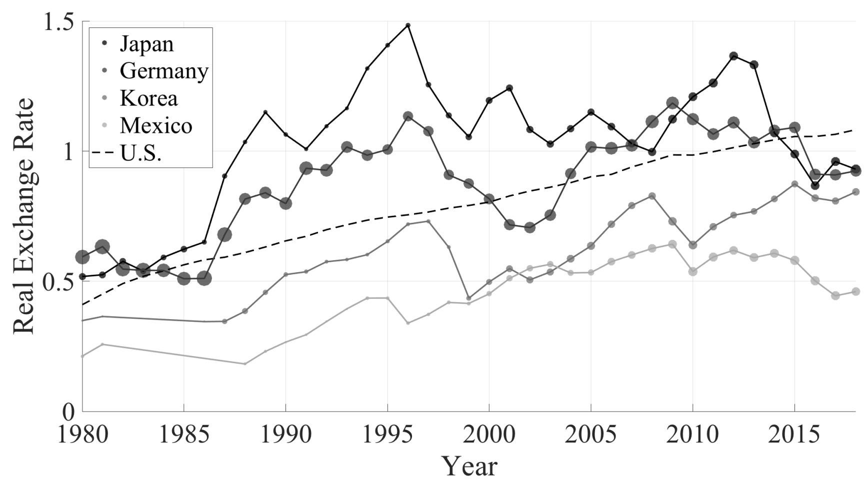
2.2 Price Instrument

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 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

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.

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. 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. 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 14.09. We cluster the standard errors at the make level. The first stage implies a pass-through of Real XR to prices of 0.141, 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*	4.073 (1.085)	-0.722 (0.232)	–	–
Price			-0.022 (0.005)	-0.177 (0.063)
Height	-15.432 (3.559)	-0.417 (0.465)	-0.784 (0.488)	-3.153 (1.245)
Footprint	-7.635 (4.543)	2.244 (0.535)	2.080 (0.521)	0.890 (1.012)
Weight	31.866 (4.424)	-1.855 (0.565)	-0.965 (0.559)	3.795 (2.186)
Horsepower	17.335 (2.615)	-0.182 (0.153)	0.473 (0.146)	2.891 (1.114)
Miles/$	4.310 (1.325)	-0.141 (0.197)	0.075 (0.211)	0.623 (0.418)
No. Trims	-1.280 (0.228)	1.235 (0.054)	1.197 (0.054)	1.008 (0.114)
Yrs. Design	0.033 (0.048)	-0.073 (0.013)	-0.072 (0.014)	-0.067 (0.015)
Release Year	-0.795 (0.442)	-0.272 (0.072)	-0.303 (0.078)	-0.413 (0.124)
Sport	4.737 (0.930)	-0.696 (0.099)	-0.557 (0.091)	0.144 (0.335)
Electric	7.726 (1.762)	-1.044 (0.256)	-0.735 (0.246)	0.326 (0.579)
Truck	-3.953 (1.521)	-0.553 (0.115)	-0.652 (0.115)	-1.254 (0.352)
SUV	-1.003 (1.188)	0.558 (0.105)	0.545 (0.112)	0.381 (0.229)
Van	-2.454 (1.569)	-0.044 (0.143)	-0.118 (0.155)	-0.479 (0.327)
Constant	390.230 (133.366)	-21.062 (11.910)	-16.934 (3.165)	-42.639 (14.079)
Mean Own Price Elas.	–	–	-0.808	-6.37
Implied Pass-through	0.125 (0.026)			
First Stage F-Stat	14.09			

Notes: Unit of observations: year make-model, from 1980 to 2018. Number of observations: 9,694. All specifications include year and make fixed effects. Standard errors clustered by make in parentheses. Car characteristics in logs and price is in 2015 $10,000.
* 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.

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 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 cars is crucial for identifying unobserved heterogeneity in the demand model we present in Section 2.

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

In this section we describe 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

[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.

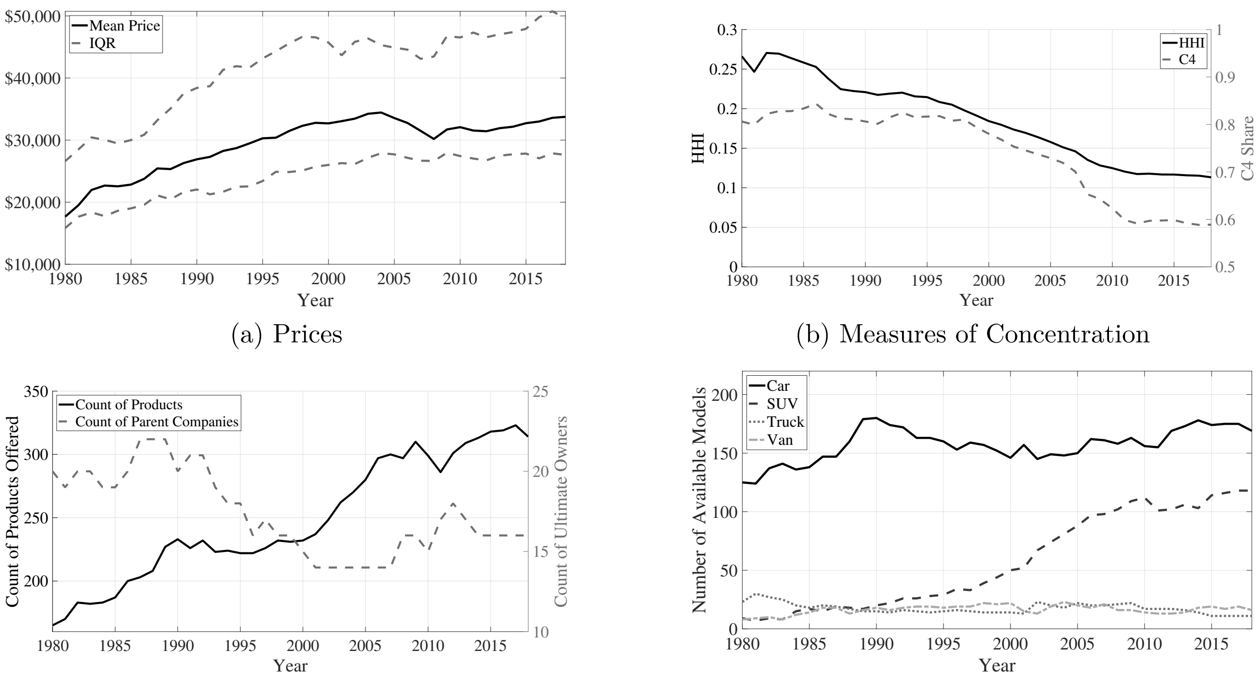
Table 3: Second Choices, Selected Examples

Car	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.

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 Figure 2c 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

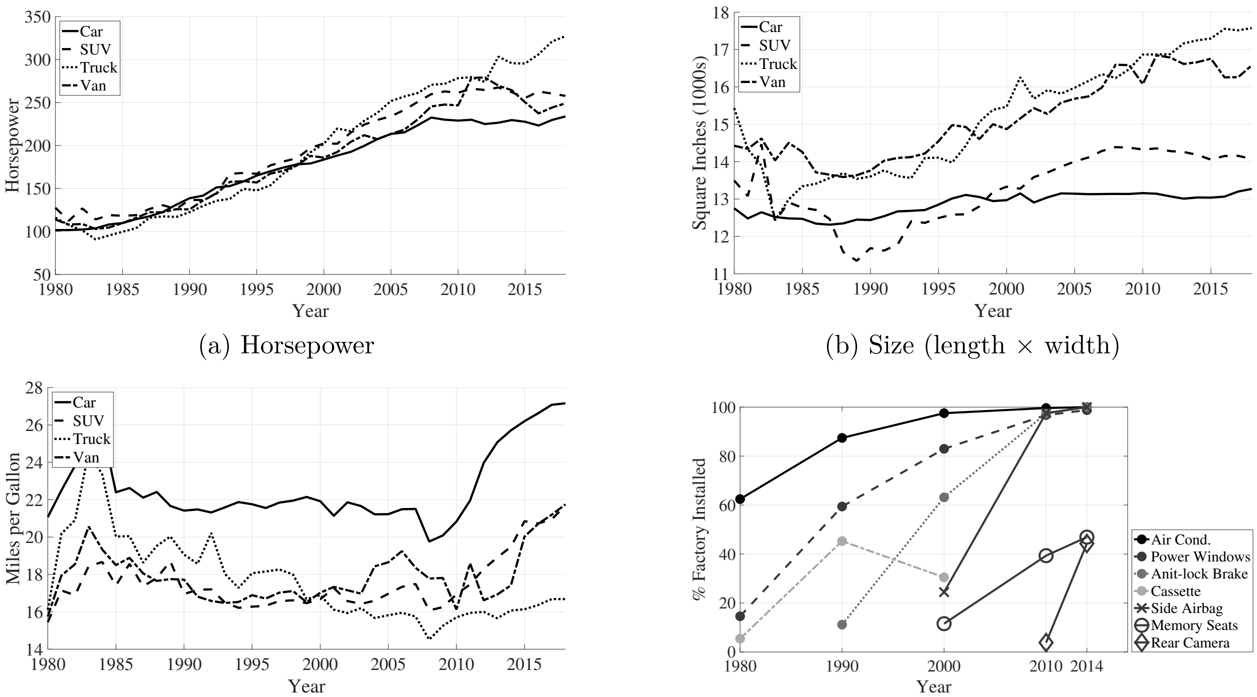
Notes: Panel (a): average price is not weighted by sales. Panel (b): HHI and C4 are defined at the parent company level, e.g. Honda is the parent company of the Honda and Acura brands. In Panel (c), the number of products corresponds to a model available in a given year in our sample. The style definitions 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 preference 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_j), price (p_j), an unobserved vehicle specific term (ξ_{jt}), and an idiosyncratic consumer-vehicle specific term (ϵ_{ij}).

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

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

[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.

Pakes et al. (1993b) and add the restriction that

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

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 from γ_t following 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:

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

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

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]

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,

[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.

[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.

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

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, $\mathcal{J}_t^m$, 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:

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

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

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

[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. (1999) 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.

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.

The full estimation procedure is described in Appendix A. 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.

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 less price sensitive. Larger household have stronger preferences for vans and vehicle footprint. Rural households have a stronger preference for trucks.

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

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. 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).

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

[8] See Table 8 for a complete list of micromoments. See Berry et al. (2004) for details of the procedure.

Table 4: Coefficient Estimates

				Demographic Interactions						
	$\bar{\beta}$	σ		Income	Inc.^{2}	Age	Rural	Fam. Size 2	FS 3-4	FS 5+
Price	-3.200	–		0.094	-0.464	2.068	–	–	–	–
	(0.065)			(0.009)	(0.112)	(0.104)				
Van	-7.292	5.348		–	–	–	–	1.668	3.563	5.653
	(0.24)	(0.102)						(0.144)	(0.151)	(0.202)
SUV	-0.083	3.646		–	–	–	–	–	–	–
	(0.072)	(0.064)								
Truck	-7.533	6.309		–	–	–	3.009	–	–	–
	(0.284)	(0.188)					(0.313)			
Footprint	0.517	1.884		–	–	–	–	0.483	0.463	0.645
	(0.033)	(0.044)						(0.045)	(0.048)	(0.06)
Horsepower	1.094	1.249		–	–	–	–	–	–	–
	(0.029)	(0.123)								
Miles/Gal.	-0.945	1.636		–	–	–	–	–	–	–
	(0.053)	(0.071)								
Luxury	–	2.627		–	–	–	–	–	–	–
		(0.028)								
Sport	-3.066	2.62		–	–	–	–	–	–	–
	(0.062)	(0.043)								
Electric	-5.342	3.835		–	–	–	–	–	–	–
	(0.168)	(0.108)								
EuroBrand	–	1.923		–	–	–	–	–	–	–
		(0.03)								
USBrand	–	2.14		–	–	–	–	–	–	–
		(0.038)								
Constant	-3.164	–		0.362	–	–	–	–	–	–
	(0.095)			(0.032)						
Height	-1.819	–	–	–	–	–	–	–	–	–
	0.038									
Curbweight	0.432	–	–	–	–	–	–	–	–	–
	0.033									
No. Trims	1.122	–	–	–	–	–	–	–	–	–
	0.029									
Yrs Redesign	-0.118	–	–	–	–	–	–	–	–	–
	0.006									
Release Yr.	-0.417	–	–	–	–	–	–	–	–	–
	0.001									

Notes: Brand and year dummies included. Footprint is log vehicle length times height in square inches. We estimate separate βs for length, height, and width that are not displayed. The number of years since the vehicle has been redesigned, 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.

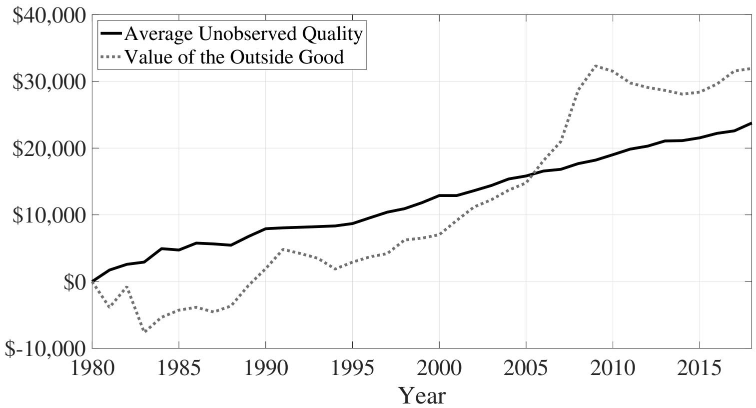
Table 5: Own Price Elasticities by Income Quintile Over Time

	Income Quintile				
Year	1	2	3	4	5
1980	-5.96	-5.78	-5.49	-5.13	-4.30
2000	-8.24	-7.83	-7.40	-6.88	-6.21
2018	-9.37	-8.56	-7.69	-6.90	-6.46

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

business cycle factors or changes in the utility of not purchasing a new car.

Figure 4: 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.

Figure 4 displays the results of this decomposition. We find that unobservable vehicle quality is steadily increasing roughly linearly. The value of the outside option generally increases over the time period with noticeable deviations from trend during the 1990-1991 and 2007-2009 recessions. Car durability is likely an important aspect for both of these trends. We would expect increased car durability to increase the value of a car, and since this is an unobserved component of quality, this effect should appear in our quality adjustment, τ. Between 1980 and 2018, data from the National Highway Traffic Safety Administration implies that the average time a consumer keeps a new car has risen from 3.9 to 5.9 years, consistent with increasing durability. This is part of the improvement in unobserved quality captured by our quality adjustment along with improvements in 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 aggregate part of the time effect along with business cycle fluctuations and the desirability of alternative transportation options. These series are broader than durability, however. Other unobserved features of cars include improved safety and electronic features such as rear view cameras and Bluetooth audio systems and improved comforts such as power or heated seats. 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.

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

			Alternative Specifications	
	Data	Model	Logit	Only Demographics
Van	0.71	0.71	-0.01	0.01
SUV	0.64	0.64	-0.01	-0.01
Truck	0.84	0.80	-0.02	-0.01
logSizeLW	0.71	0.69	-0.02	0.00
Horsepower	0.60	0.59	-0.01	0.01
MilesPerGallon	0.65	0.65	-0.01	0.00
Luxury	0.48	0.49	-0.01	0.00
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	0.00
USBrand	0.48	0.47	-0.01	-0.01

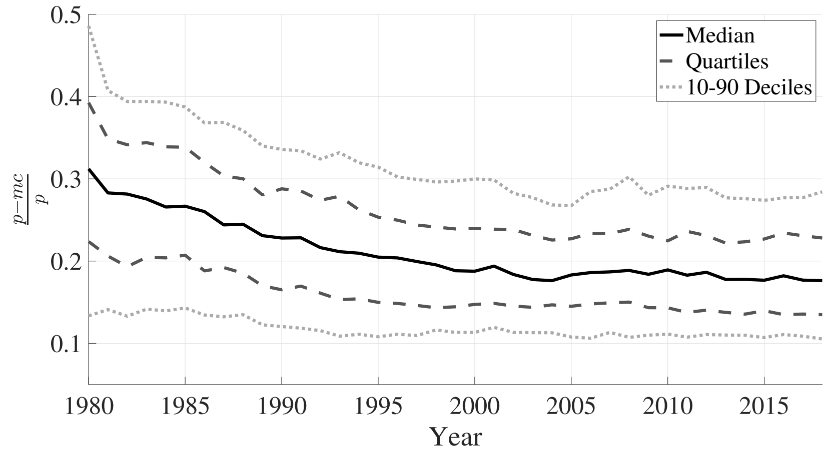
Notes: Data from MaritzCX survey, 1991, 1999, 2005, 2015. The numbers are the average across these four years. “Model” column represents the predictions from the model presented in Table 4. The “Logit” column are contains model predictions from a simple logit demand specification. The “Only Demographics” 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 5 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.

In Figure 6 we display average 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

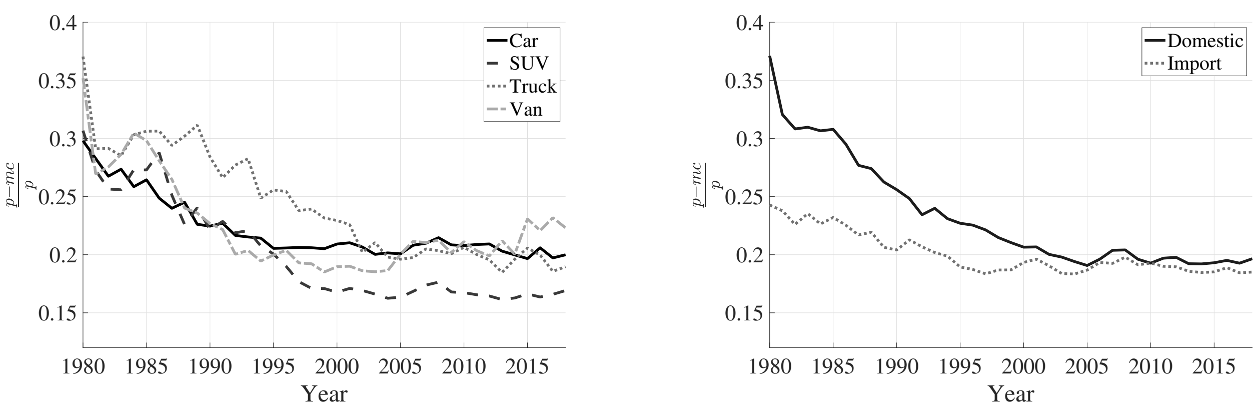
Figure 5: Markups Over Time



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

number of SUVs available nearly tripled during this time and our demand estimates imply strong within category substitution. Turning to panel (b) in Figure 6, 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 6: Markups over Time



(a) Markups by Vehicle Style

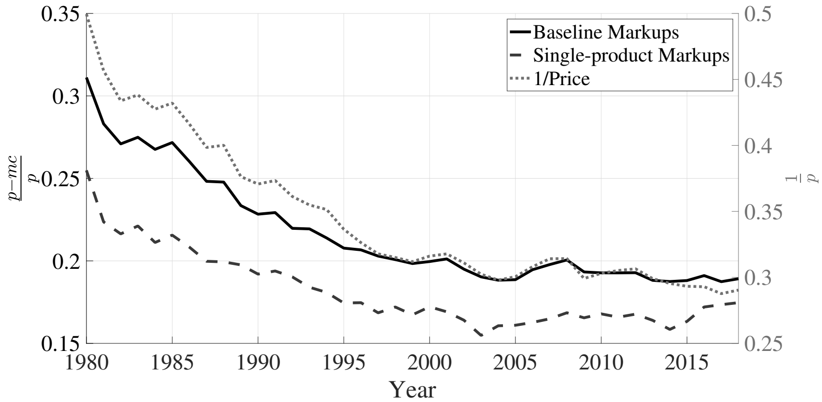
(b) Markups by Import Status

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 7: 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.

Figure 7 or assuming industry wide collusion in Figure 8. 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 with respect to price are roughly constant. This combination implies that markups decrease. To illustrate this, we also plot $1/p$ in Figure 7. 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. The markup over time is not a conceptually attractive proxy for welfare when the product set is changing.[9] In our estimates, the change in markups over time is fundamentally related to the change in car quality. We will thus focus on the model's measures of welfare and surplus over time to assess industry performance in Section 6.

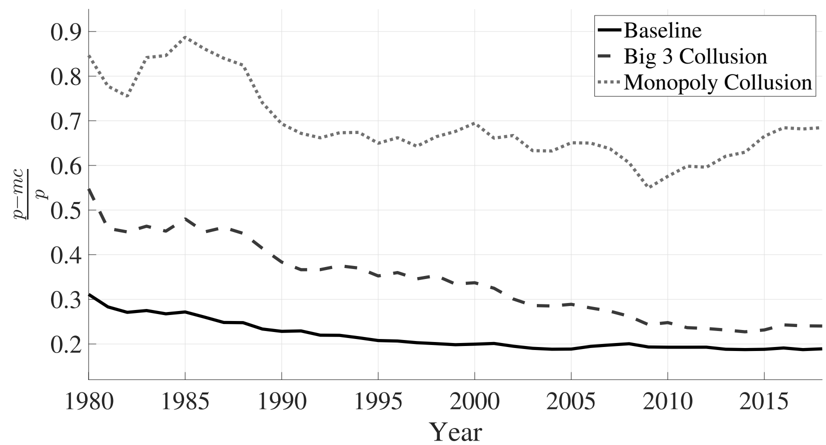
5.4 Robustness to Conduct Assumption

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

[9]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.

the first case, we assume the Big Three US auto manufacturers (G.M., Ford, and Chrysler) collude on prices for our entire sample.[10] 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 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 time.

Figure 8: 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 8 establishes that under a variety of constant conduct assumptions, markups decline over time. However, it is possible that cartel could form 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.

[10]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.

Table 7: Average Markups with Different Cartel Assumptions

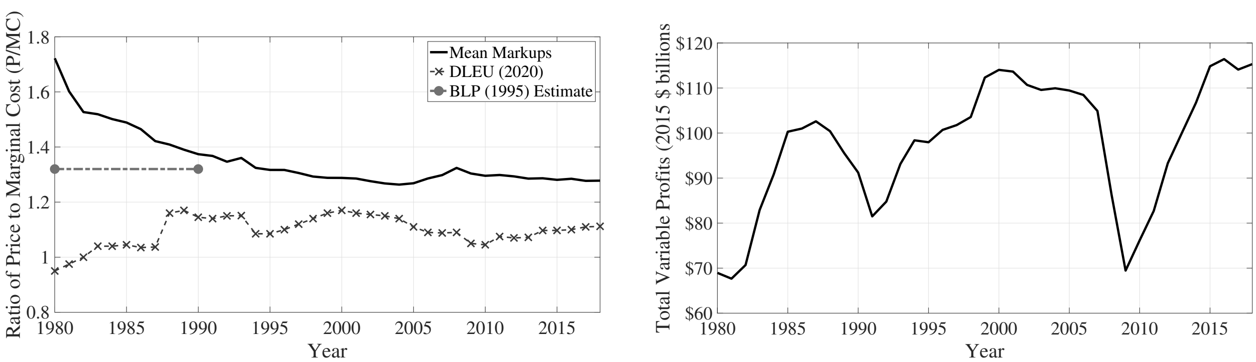
	Average Markup
1980 Baseline	0.311
2018 Baseline	0.196
2018 Cartel Membership	
GM + Ford + Toyota	0.222
Top 3 + Fiat	0.264
Top 4 + Honda	0.290
Top 5 + Nissan	0.338

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

5.5 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.[11] 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 9a. 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 9: Comparison to De Loecker et al. (2020)



(a) Price over Marginal Cost

(b) Total Variable Profits

Notes: Panel (a) displays our estimate, the estimate for 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 9a. 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

[11] 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.

the conduct assumption of static Nash pricing does not hold.[12] The production based estimates could be off from the truth because 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 difference between marginal and average costs. Furthermore, the underlying data differ in that the Compustat based estimates in 9a 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 a an increase in the 1980's, a dip and recovery in the 1990's, and a dip and recovery around the Great Recession.

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. Instead, an important advantage of our demand side approach is that it provides a direct measures of consumer surplus which are not available without an estimated demand system. For the remainder of the paper, we will use our approach 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. Therefore, drawing conclusions about welfare by comparing markups or concentration over time can be misleading because products are improving over time. Instead, 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

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

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.[13]

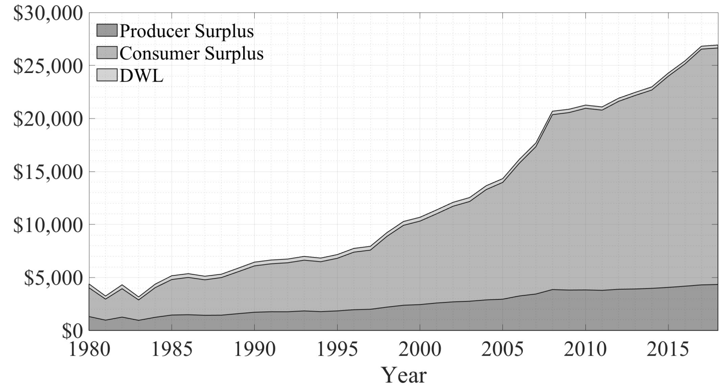
In Figure 10 we plot estimated consumer surplus ($\widetilde{CS}_t$), producer surplus, and deadweight loss over the sample period. Total surplus rises roughly \$20,000 per household, from \$5,000 to a little over \$25,000. Overall, the market is very efficient, with deadweight loss representing a small portion of total 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 11 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 11a displays consumer surplus, in 2015 dollars. Under the alternative measure, consumer surplus is relatively flat over the period with marked troughs in the early 1980s, early 1990s, and 2009, corresponding to the three

[13]Deadweight loss is computed by subtracting the sum of estimated consumer and producer surplus from the consumer surplus calculated when products are priced at marginal cost.

[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.

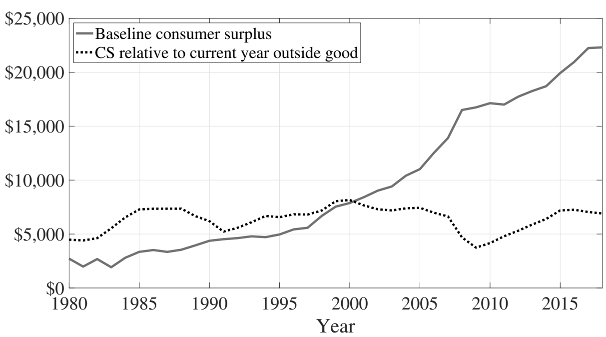
Figure 10: Consumer Surplus, Producer Surplus, and Deadweight Loss



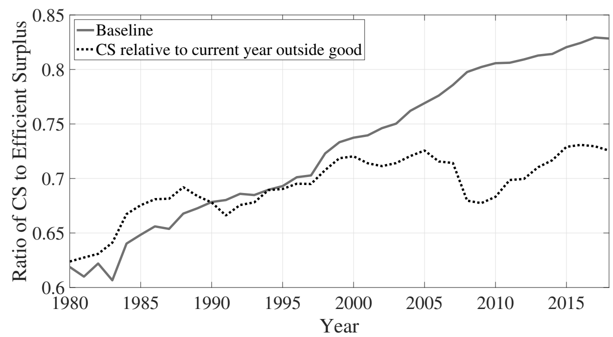
Notes: Consumer surplus, producer surplus and deadweight loss. Consumer surplus in the compensating variation procedure detailed in the text. Deadweight loss is computed by netting consumer and producer surplus form efficient surplus, defined as the surplus available when prices equal marginal costs.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

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 4. Figure 11b 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. We measure total efficient surplus by computing surplus when prices equal marginal costs. 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 0.83.

Figure 11: Consumer Surplus Comparison



(a) Consumer Surplus Comparison



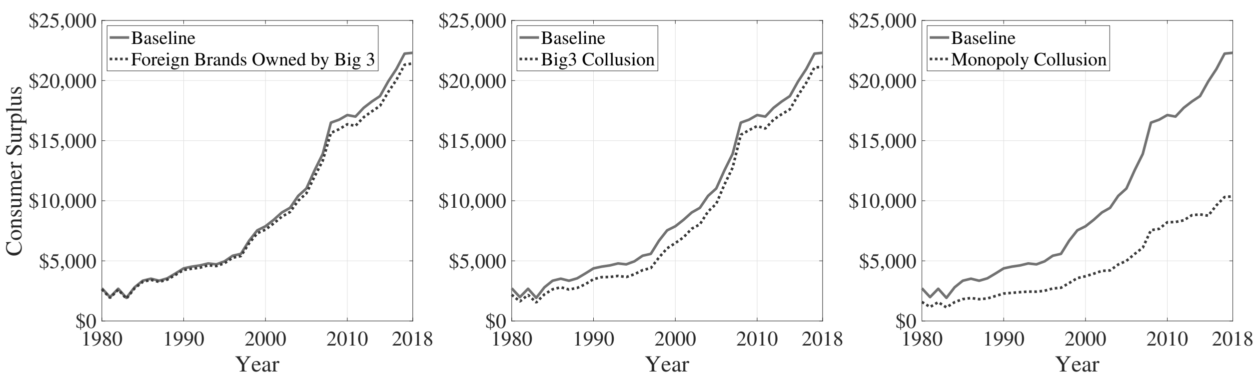
(b) CS as a Share of Total Available Surplus

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, SUVs are more popular than sedans, 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.

Figure 12: 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.

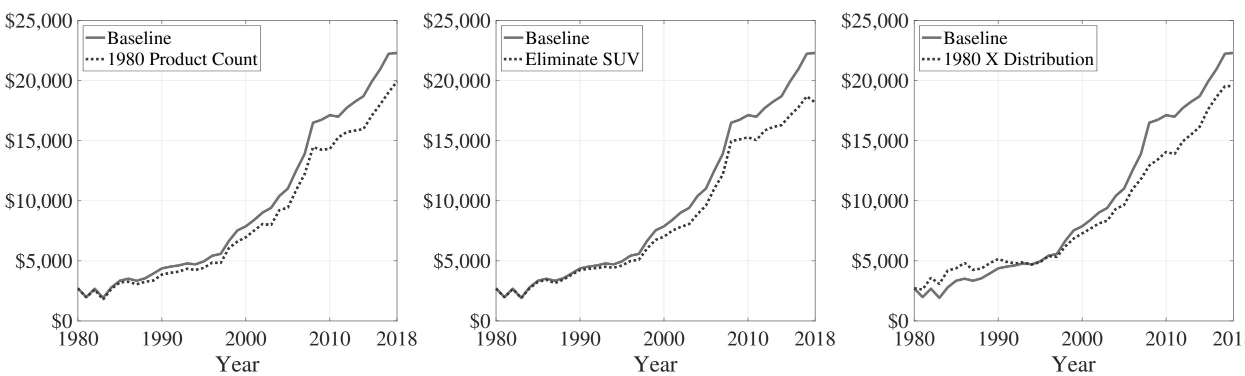
Mechanism 1: Increased competitive pressure form foreign brands. It is possible that the increase in foreign brands competing in the US led to downward pressure on prices that benefited consumers.[15] To understand this mechanism, we simulate an alternative scenario where we assume all vehicles sold 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.

[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.

The results, in terms of consumer surplus, are presented in the left panel of Figure 12. Throughout this section, the sold 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 did not contribute much to the rise in consumer surplus. Again, this is consistent with competition kicking in 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 does not increase, but the ownership configuration which eliminates global competition does not achieve this.

Figure 13: 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 reason for the increase in consumer surplus could be the increase in the number of available products. Consumer welfare can increase 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 13. 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

[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.

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. As can be seen in Figure 3, vehicles become more attractive between 1980 and 2018 in observable characteristics such as efficiency and power, and harder-to-measure characteristics such as safety, technology, durability, and aesthetic design improvements. Furthermore, the number of SUV's available to consumers increased noticeably. In our model, these features are captured in both observed characteristics and an unobserved vertical quality term, ξ. In the middle and right panels of Figure 13, we examine the observable characteristics of vehicles. In the middle panel, we eliminate all SUV's which enter into the market. SUVs represent a new and popular segment of the automobile market that was essentially unavailable in 1980. While counterfactual consumer surplus is lower, like the other mechanisms discussed, this channel can only explain a small portion of the increase in consumer surplus.

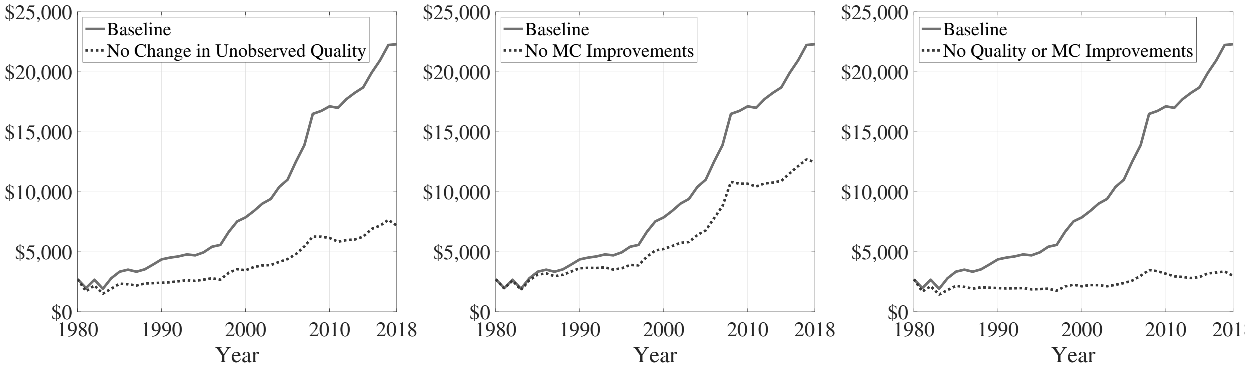
Another notable trend in the industry has been the general growth in car characteristics such as size and horsepower. In the right panel, we scale the distribution of horsepower, MPG, and footprint year-by-year to match the mean and variance of these characteristics in the 1980 choice set, holding marginal costs of production fixed. 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.

However, we do find a large effect due to the improvements in unobservable vehicle quality. In the left panel of Figure 14, 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.

Mechanism 4: Decreasing costs. We find that marginal costs of producing a car with fixed characteristics experiences a steady decline over time. Specifically, we regress the inferred marginal cost at the vehicle-year level on product characteristics and a time trend, and estimate a negative trend. In the middle panel of Figure 14 we eliminate the downward trend in marginal costs and recompute adjusted surplus measures. Since the trend is negative, this removes the benefits from decreasing marginal costs for a fixed set of product characteristics over time. We find that welfare increases by about half as much as in the baseline. Thus falling marginal costs are also a significant driver of the measured increase in consumer surplus.

Finally, in the right panel of Figure 14, we combine the left and middle panel counterfactuals and simulate a world where neither the unobservable product quality increases nor do marginal

Figure 14: 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.

costs fall by the time trend. This combination almost entirely eliminates the measured increased 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. We do not analyze adjacent markets such as the market for financing or the value chain between suppliers, manufacturers, and dealerships. Profits and firm behavior in these markets are linked and could be offsetting the changes we measure here. Finally, 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

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

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,

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

We can now construct the moments for our estimator of θ. Let $\mathscr{s}_{ij}(\theta) = \mathscr{s}_{ij}(\theta, \delta(\theta))$. 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]

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

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]

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

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

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

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

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

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.

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 $\hat{\gamma}_t = \hat{\iota}_t - \hat{\tau}_t$.