THE EVOLUTION OF MARKET POWER IN THE U.S. AUTOMOBILE INDUSTRY*

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We construct measures of industry performance and welfare in the U.S. automobile market from 1980 to 2018. We estimate a demand model using product-level data on market shares, prices, and attributes, 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 trends in market structure and the composition of products. 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 improved product quality and improved production technology. *JEL codes:* L11, L62, D43.

I. Introduction

From 1980 to 2018, the U.S. automobile industry experienced numerous technological and regulatory changes and its market structure changed dramatically. The goal of this article is to examine whether these changes led to discernible changes in industry performance. This work complements a recent academic and policy literature analyzing long-term trends in market power and sales concentration from a macroeconomic perspective (Autor et al. 2020; De Loecker, Eeckhout, and Unger 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 period (Economist 2016; Covarrubias, Gutiérrez, and Philippon 2020). Our estimates indicate a significant decline in markups over the past four decades, in contrast to estimates computed using methods and data from the recent macroeconomics literature.

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Furthermore, our approach—also in contrast to the recent literature—admits a measure of consumer surplus over time. We find that consumer welfare in the U.S. automobile market has increased significantly over this period, primarily due to improvements in product quality and production technology.

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 multiproduct automobile manufacturers. The key inputs into the demand estimates are aggregate data on prices, market shares, and vehicle characteristics over time, microdata on the relationship between demographics and car characteristics over time, microdata on consumers' stated second choices, and the use of the real exchange rate between the United States and product origin countries as an instrumental variable for endogenous prices. With the demand system in hand, we infer product-level markups from the first-order condition of each firm's profit maximization problem.

We find that median markups as defined by the Lerner index ($L = \frac{p-mc}{p}$) fell from 0.325 in 1980 to 0.185 by 2018 (Figure VI, Panel A). However, as we detail below, although markups are a useful proxy for market efficiency when products are fixed over time, they are a conceptually unattractive measure over long periods of time when products change. We use our model to consider trends in consumer and producer surplus directly. To quantify changes in welfare over time, we use a decomposition from Pakes, Berry, and Levinsohn (1993) to develop a measure of consumer surplus that is robust to changes in the attractiveness of the outside good. This 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, for example, business cycle effects such as monetary policy or changes in alternative transportation options. We find that the fraction of efficient surplus (the sum of producer surplus, consumer surplus, and deadweight loss) going to consumers went from 0.62 in 1980 to 0.82 by 2018 and that average consumer surplus per household increased by roughly $8,000 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 the combined valuation 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, antilock breaks, rearview cameras, driver assistance systems). Improvements on these dimensions are quantitatively large. In addition, we estimate improved production technology from variation in marginal cost over time controlling for product attributes. Counterfactuals that eliminate the observed increase in import competition or the increase in the number of vehicle models have small to moderate effects on consumer surplus. Counterfactuals that eliminate the increase in automobile quality and the technological improvements in production have the greatest effect on consumer surplus.

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, for robustness, we present a number of alternative assumptions on conduct, all of which indicate declining markups when conduct is fixed over time. 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 for the automobile manufacturers.

By studying long-run trends in market power and market efficiency using the workhorse toolbox of supply and demand estimation, we provide an alternative perspective on the analysis of the recent literature on the rise in aggregate markups based on production-side modeling and accounting data on revenues and costs, for example De Loecker, Eeckhout, and Unger (2020) and various subsequent studies. This approach infers markups at the firm level under the assumption that firms optimally choose the quantity of variable inputs in production to minimize costs. The assumptions of these two approaches are nonnested; we provide a comparison of our markup estimates in the U.S. automobile industry with those constructed by De Loecker, Eeckhout, and Unger (2020) in Section V.F. Our perspective is rooted in the methods developed in industrial organization that grew out of the critique of the structure-conduct-performance literature, for example, Demsetz (1973), and for a historical perspective see Berry, Gaynor, and Scott Morton (2019). Our approach also allows for an understanding of the mechanisms that contribute to trends in market power and consumer surplus. In particular, we highlight the importance of characterizing consumer welfare, which is only possible by estimating demand curves.

This work thus complements research that raises measurement issues and proposes alternatives in the production paradigm, such as Traina (2018), Raval (2023), Demirer (2022), Bond et al. (2021), Doraszelski and Jaumandreu (2021), and Foster, Haltiwanger, and Tuttle (2022). Although we focus on a single industry, our results suggest that more work should be done to carefully measure market power and welfare in important industries to provide an alternative measurement from the production approach and identify the mechanisms that drive trends in market power and efficiency.

There are now other recent examples of researchers using demand and supply to characterize trends in markups in specific industries.[1] Brand (2021) and Döpper et al. (2023) analyze multiple grocery categories for a selection of retail outlets over the period 2006 to 2017 and 2019, respectively. Miller et al. (2022) analyze the cement industry over 1976 to 2016. Ganapati (2021) studies the wholesaling sector over 1997 to 2007. Across a variety of industries, these papers point out that technological changes over decades affecting product qualities and costs are large and important to control for when inferring market power. This article corroborates this finding in the auto industry by documenting the large changes in product quality over time as well as significant cost-reducing technological improvements. Relative to these papers, this article uses household-level data on purchases, demographics, and second choices to estimate a demand specification with rich heterogeneity and employs standard instrumental variable identification strategies. This study also compares its markup estimates with production function–based estimates as reported in De Loecker, Eeckhout, and Unger (2020) and analyzes the determinants of the change in consumer surplus over time. Bet (2021) compares markup estimates from a demand approach with those from a production approach for domestic airlines and finds that under Nash-Bertrand pricing, markups from the demand approach are flat for large carriers, while under the production approach, markups for large carriers are increasing over the

1. In an earlier contribution, Berry and Jia (2010) analyzed changes in demand and market power in the U.S. airline industry between 1999 and 2006.

period 2013 to 2019. Relative to these other papers, our work estimates the role of technological progress in improving consumer surplus by decomposing over time changes in demand shocks into improvements in unobservable quality and changes in the value of the outside option. This decomposition is important for interpreting the economics of how changing prices and markups translate into consumer welfare when products and technology change over time.

Our research is also closely related to Hashmi and Biesebroeck (2016), who model dynamic competition and innovation in the world automobile market using a logit model over the period 1982 to 2006. Relative to their work, this article focuses 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 article uses microdata and second-choice data to estimate demand following Bordley (1993) and Berry, Levinsohn, and Pakes (2004), uses a different instrumental variable to account for price endogeneity, and decomposes time effects in demand separately into changes in unobservable quality and changes in the value of the outside option.

II. 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.

II.A. Automobile Market Data

Our primary source of data is information on sales, manufacturer suggested retail prices (MSRP), and characteristics of new cars and light trucks sold in the United States over 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 nonstandard across years and required multiple layers of digitization and rechecking. 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 the United States), and model redesign years. Prices in all years are deflated to 2015 US$ using the core consumer price index. To construct market shares, we define the market size as the number of households in the United States divided by 2.5, which reflects the fact that the average household owns nearly two cars and the average tenure of car ownership during this time period is roughly five years.

1. *Product Aggregation.* Vehicles sold in the United States 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 is 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, Levinsohn, and Pakes (1995 (BLP), 2004), Goldberg (1995), and Petrin (2002). We aggregate price and product characteristics by taking the median across trims.

Table I displays 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 6,130 cars, 2,243 SUVs, 680 trucks, and 641 vans in our sample.[2] The average car has 52,089 sales in a year, and the average truck has 140,207 sales. Trucks and vans are more likely to be from U.S. brands and less likely to be assembled outside of the United States 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 III.

2. We use Ward's 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 Ward's designations. We designate all other styles (sedan, coupé, wagon, hatchback, convertible) as car. Some models are produced in multiple variants. For example the Chrysler LeBaron has been available as a sedan, coupé, 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.

TABLE I
SUMMARY STATISTICS

	Mean	Std. dev.	Min	Max		Mean	Std. dev.	Min	Max
Cars, N = 6,130					**SUVs, N = 2,243**				
Sales	52,088.60	72,750.83	10.00	473,108.00	Sales	51,629.61	66,932.79	10.00	753,064.00
Price	35.85	18.76	11.14	99.99	Price	40.41	14.94	12.75	96.94
MPG	22.67	6.82	10.00	50.00	MPG	18.01	4.98	10.00	50.00
Horsepower	178.21	83.41	48.00	645.00	Horsepower	232.33	74.92	63.00	510.00
Height	55.76	4.21	43.50	107.50	Height	69.01	4.38	53.00	90.00
Footprint	12,870.08	1,710.41	6,514.54	21,821.86	Width	13,790.90	1,785.69	8,127.00	18,136.00
Curb weight	3,181.94	639.51	1,488.00	6,765.00	Curb weight	4,246.05	854.30	2,028.00	7,230.00
U.S. brand	0.40	0.49	0.00	1.00	U.S. 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	0.01	0.12	0.00	1.00
Trucks, N = 680					**Vans, N = 641**				
Sales	140,207.22	184,123.33	12.00	891,482.00	Sales	59,103.39	86,940.25	10.00	891,482.00
Price	27.81	9.82	12.02	69.43	Price	36.05	17.13	11.14	99.99
MPG	17.83	4.36	10.00	50.00	MPG	20.94	6.58	10.00	50.00
Horsepower	189.17	90.31	44.00	403.00	Horsepower	192.18	83.88	44.00	645.00
Height	68.39	6.33	51.80	81.00	Height	60.95	8.41	43.50	107.50
Footprint	15,086.14	2,478.91	8,437.30	20,000.00	Footprint	13,392.63	1,968.92	6,514.54	21,821.86
Curb weight	4,043.42	1,114.94	1,113.00	7,178.00	Curb weight	3,561.21	897.77	1,113.00	8,550.00
U.S. brand	0.65	0.48	0.00	1.00	U.S. brand	0.44	0.50	0.00	1.00
Import	0.35	0.48	0.00	1.00	Import	0.55	0.50	0.00	1.00
Electric	0.00	0.00	0.00	0.00	Electric	0.02	0.13	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 US$. Physical dimensions are in inches, and curb weight is in pounds.

II.B. 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 vehicle 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, version 9.1, variable `pl_con`, lagged by one year to reflect planning horizons. Following Feenstra, Inklaar, and Timmer (2015), we refer to this as the real exchange rate (RXR). RXR is equal to the purchasing power parity (PPP) exchange rate relative to the United States divided by the nominal exchange rate relative to the United States. RXR 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 raise the RXR via the PPP rising. Therefore, the RXR 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 United States, thereby providing another avenue of positive covariation between the RXR and retail prices in the United States. Exchange rates were used as instrumental variables for car prices in Goldberg and Verboven (2001), which is focused on the European car market, and in Berry, Levinsohn, and Pakes (1999), along with wages. In Figure I, we display the lagged RXR for the most popular production countries, where the size of the plot marker is proportional to the number of products sold from each country and the black dashed line represents the U.S. price level. Although our measure of RXR is relative to the United States, U.S. RXR is also changing over time due to inflation.

We demonstrate the behavior of the RXR instrumental variable in a simple setup in Table II. We estimate a logit model of demand, as in Berry (1994), first via OLS and then using 2SLS with RXR as an instrumental variable for price. We include make fixed effects and year fixed effects. Within make there is variation in real exchange rates within and across time. Within time variation is due to the fact that different models of the same make are assembled in different countries. For example, BMW assembles

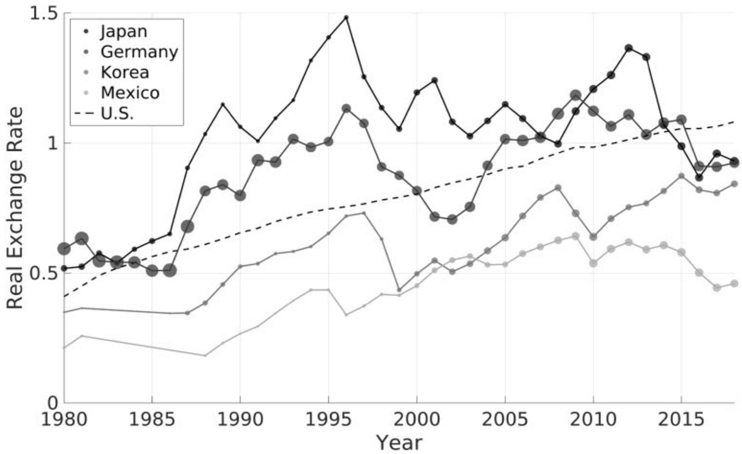


FIGURE I

Real Exchange Rates

Lagged real exchange rates are from Penn World Tables 9.1. The size of dots corresponds to the relative number of sales by production country, except for the United States.

vehicles for the U.S. market in Germany and the United States, General Motors has produced U.S.-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 vehicles in different countries. The first column in Table II shows the first-stage relevance of the instrumental variable. The sign is positive as predicted by the theory with a first-stage F-statistic of 14.09. We cluster the standard errors at the make level. The first stage implies a pass-through of RXR to prices of 0.117, 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 using 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 II

LOGIT DEMAND

	First stage	Reduced form	OLS	IV
Price			−0.334 (0.042)	−1.696 (0.598)
RXR	0.411 (0.110)	−0.697 (0.232)		
Height	−0.199 (0.048)	−0.064 (0.066)	−0.120 (0.069)	−0.401 (0.161)
Footprint	−0.117 (0.066)	0.348 (0.081)	0.318 (0.082)	0.149 (0.149)
Horsepower	0.768 (0.116)	−0.097 (0.070)	0.149 (0.067)	1.206 (0.472)
MPG	0.113 (0.036)	−0.062 (0.057)	−0.018 (0.062)	0.130 (0.116)
Curb weight	0.803 (0.111)	−0.493 (0.142)	−0.233 (0.140)	0.868 (0.541)
Num. of trims	−0.115 (0.020)	1.097 (0.045)	1.060 (0.044)	0.902 (0.091)
Release year	−0.081 (0.040)	−0.173 (0.054)	−0.195 (0.056)	−0.311 (0.091)
Yrs. since design	0.000 (0.012)	−0.145 (0.017)	−0.145 (0.017)	−0.144 (0.024)
Sport	0.480 (0.090)	−0.679 (0.105)	−0.523 (0.102)	0.134 (0.323)
Electric	0.765 (0.176)	−1.031 (0.255)	−0.791 (0.245)	0.267 (0.560)
Truck	−0.416 (0.154)	−0.485 (0.099)	−0.631 (0.107)	−1.190 (0.359)
SUV	−0.111 (0.117)	0.561 (0.100)	0.515 (0.105)	0.372 (0.214)
Van	−0.268 (0.161)	0.037 (0.126)	−0.060 (0.143)	−0.417 (0.330)
Mean own price elas.	—	—	−1.204	−6.107
Implied pass-through	0.117 (0.032)			
First stage F-statistic	14.086			

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 are in parentheses. All continuous car characteristics are in logs and price is in 2015 $10,000. Variables are logged and standardized.

II.C. Consumer Choices and Demographics

We collect individual-level data on car purchases and demographics from two data sources: the Consumer Expenditure Survey (CEX) and 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 1980–2005 with an average of 1,014 observations a year. MRI covers 1992–2018 with an average of 2,005 observations a year. We construct micromoments from these data to use as targets for the heterogeneous agent demand model, following Goldberg (1995), Petrin (2002), and Berry, Levinsohn, and Pakes (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 has a larger family size suggests families value size more than nonfamilies. 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 place higher value on characteristics that come in higher-priced cars. That rural households are more likely to purchase a truck suggests stronger preference for features of trucks by rural households.

To approximate the distribution of household demographics, we sample from the CPS, which contains the demographic 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 account for these trends by explicitly including evolving consumer heterogeneity in income, family size, and rural status as part of our model.

II.D. Second Choices

We obtain data on consumers' reported second choices from MaritzCX, 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. (2023) and Leard (2022), and are similar to the survey data used in

TABLE III
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 C/K Pickup	0.35
Honda Accord	Toyota Camry	Nissan Maxima	0.19
Dodge Caravan	Ford Aerostar	Plymouth Voyager	0.15
Mercedes-Benz E Class	BMW 5 Series	Lexus LS	0.17
Toyota 4Runner	Ford Explorer	Nissan Pathfinder	0.34
Nissan 300ZX	Alfa Romeo 164	Chevrolet Corvette	0.20
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	Dodge 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 PHV	Chevrolet Volt	Nissan Leaf	0.32

Notes. The data are from MaritzCX surveys in 1991, 1999, 2005, and 2015. Vehicles selected are high-selling vehicles that represent a range of styles and attributes. The last column displays diversion to the two most popular second choices, conditional on diversion to any vehicle.

Berry, Levinsohn, and Pakes (2004).[3] 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 III we display information about second choices for many popular cars of different styles and features to give a sense

3. 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 who answer yes, the survey asks respondents to provide vehicle make-model and characteristics for the model most seriously considered.

for how strong substitution in 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 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% 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% of reported second choices for the Chevrolet Silverado in 1999, but the Civic and Corolla only represent 22% of second choices for the Ford Focus in 2005. The generally strong substitution toward similar vehicles is crucial for identifying unobserved heterogeneity in the demand model we present in Section IV.

III. 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. Then we discuss trends in product characteristics.

III.A. Prices and Market Structure

Inflation-adjusted average prices in the automobile industry rose from 1980 to 2018. At the same time, concentration decreased. Figure II displays these patterns. In Panel A, we document that the average MSRP rose from around $17,000 in 1980 to around $34,000 in 2018 (in 2015 US$, deflated by the core CPI). The bulk of the change in average price occurred before 2000, although the upper 25% of prices continued to rise after 2000. At the same time, the Herfindahl-Hirschman index (HHI) measured at the parent company level fell from over 2,500 to around 1,200, 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,

(A) Prices

(B) Measures of Concentration

(C) Products and Manufacturers

(D) Count of Products by Styles

FIGURE II

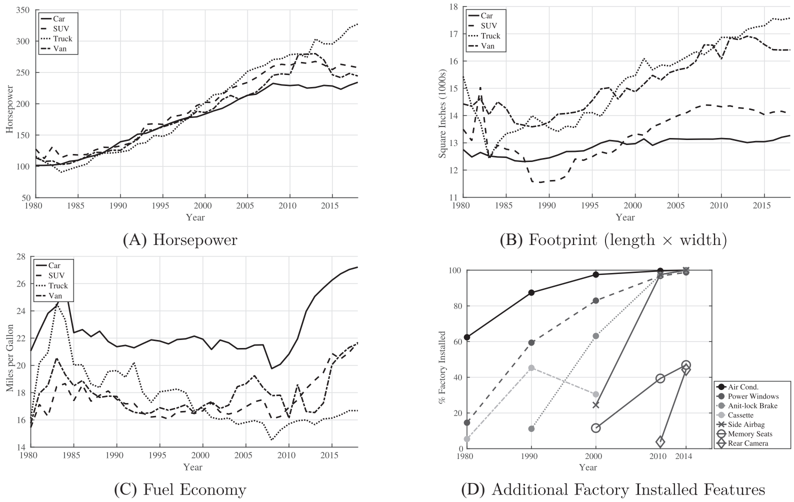
Prices and Market Structure, 1980–2018

Panel A displays share-weighted average price along with the interquartile range. Panel B: HHI (bold line and left scale) and C4 (dashed line and right scale) are defined at the parent company level, for example, 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 are from Ward's Automotive Yearbooks, and the sample selection is described in the text.

there were about twice as many products in 2018 as there were in 1980. In 1980, the "Big Three" U.S. manufacturers accounted for a large portion of sales, whereas by 2018, sales were more evenly dispersed among domestic and international firms, consistent with patterns in other manufacturing industries (Amiti and Heise 2021).

III.B. 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 nonexistent 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).



(A) Horsepower

(B) Footprint (length × width)

(C) Fuel Economy

(D) Additional Factory Installed Features

FIGURE III

Physical Vehicle Characteristics, 1980–2018

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 Ward's Automotive Yearbooks from various years. For example, in 1980 61% of "cars" sold had air conditioning.

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 II, Panel D, we display the number of products by vehicle style over time. In the early 1980s fewer than 25 SUVs were available to consumers (typically large truck-like vehicles) and after 2000 there were nearly 100 SUVs available in the market.

Figure III displays selected product attributes over time. Average horsepower and footprint (length times 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 III, Panel A. 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 that 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.

In addition, attributes not related to size and power changed substantially from 1980 to 2018. In Figure III, Panel D, we show the percent of cars (i.e., not trucks, SUVs, or vans) sold with the following features, for 1980, 1990, 2000, 2010, and 2014: air conditioning, power windows, antilock brakes, cassette player stereo system, side airbags, memory seats, and rear camera.[4] 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 became popular, disappearing by 2010. In our demand model, many of these features will be subsumed into a quality residual that summarizes all characteristics not captured by readily available data like horsepower and vehicle size.

IV. Model

Our framework is a differentiated product demand and oligopoly pricing model following Berry, Levinsohn, and Pakes (1995), which is standard in the industrial organization literature.

IV.A. Consumers

Consumer i makes a discrete choice among the J_t options in the set $\mathcal{J}_t$ 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.[5]

Utility is a consumer-specific linear index of a vector of vehicle attributes ($\mathbf{x}_{jt}$), price (p_{jt}), an unobserved vehicle-specific term

4. These data were collected from Ward's Automotive Yearbooks of the corresponding years.

5. Our model focuses on consumers' selection of a manufacturer's product. In particular, we abstract away from financing, leasing, and dealership choice.

(ξ_{jt}), and an idiosyncratic consumer-vehicle-specific term (ϵ_{ijt}).

$$u_{ijt} = \beta_{it}\mathbf{x}_{jt} + \alpha_{it} p_{jt} + \xi_{jt} + \epsilon_{ijt}. \tag{1}$$

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 preferred specification, the parameters governing these distributions are fixed over time, but we also report estimates including time-varying components to parameters of the distribution of α_i and β_i. We assume that ϵ_{ijt} are independent draws from the standard Gumbel distribution.

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 assume that $E[\tilde{\xi}_{jt}|\mathbf{z}_{jt}] = 0$, where $\mathbf{z}_{jt}$ is a vector of instruments including $\mathbf{x}_{jt}$, year dummies, and an instrument for price (i.e., RXR).

It is well known that discrete-choice models only identify utility relative to the outside good. 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, Berry, and Levinsohn (1993) and add the restriction that

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

where $\mathcal{C}_t$ is the set of *continuing* vehicles offered in both year t and $t-1$ that have not been redesigned by the manufacturer. Consider a model $j \in \mathcal{C}_t$ as a product nameplate and design generation appearing both in $t-1$ and t.[6] This restriction captures the fact that models in a model generation have substantively the same design from year to year, although it allows for idiosyncratic changes in features, marketing, or consumer taste. That is, while ξ_{jt} can change from year to year, innovations in ξ_{jt} are mean zero across years in a model generation. This restriction

6. 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.

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 equation (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.

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 III, Panel D. 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 demographics and unobserved preferences with car attributes. Our baseline specification is:

$$\alpha_{it} = \bar{\alpha} + \sum_h \alpha_h \mathrm{D}_{it}^h \tag{3}$$

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

where subscript k denotes the kth car characteristic (including a constant) and h indexes dimensions of consumer demographics (e.g., income). Allowing for observed heterogeneity allows substitution patterns to differ by demographics. The distribution of D_{it} is taken from the CPS. In practice, we do not interact every demographic with every car characteristic. See Table IV 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.

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

TABLE IV

COEFFICIENT ESTIMATES

			Demographic interactions						
	β	σ	Income	Inc. sq.	Age	Rural	Fam. size 2	FS 3–4	FS 5+
Price	−3.112	—	0.094	−0.462	2.065	—	—	—	—
	(1.124)		(0.010)	(0.133)	(0.122)				
Van	−7.614	5.538	—	—	—	—	1.737	3.681	5.840
	(0.598)	(0.133)					(0.165)	(0.176)	(0.176)
SUV	−0.079	3.617	—	—	—	—	—	—	—
	(0.339)	(0.087)							
Truck	−7.463	6.309	—	—	—	3.007	—	—	—
	(0.898)	(0.310)				(0.340)			
Footprint	0.534	1.873	—	—	—	—	0.481	0.459	0.636
	(0.261)	(0.118)					(0.053)	(0.054)	(0.054)
Horsepower	1.018	1.246	—	—	—	—	—	—	—
	(0.954)	(0.361)							
Miles/Gal.	−0.965	1.645	—	—	—	—	—	—	—
	(0.211)	(0.151)							
Luxury	—	2.624	—	—	—	—	—	—	—
		(0.047)							
Sport	−3.046	2.617	—	—	—	—	—	—	—
	(0.549)	(0.075)							
EV	−5.549	3.798	—	—	—	—	—	—	—
	(1.406)	(0.511)							
Euro. brand	—	1.921	—	—	—	—	—	—	—
		(0.054)							
U.S. brand	—	2.141	—	—	—	—	—	—	—
		(0.048)							
Constant	—	—	0.362	—	—	—	—	—	—
			(0.034)						

Notes. Brand and year dummies included. Standard errors are constructed by bootstrapping the microdata and are clustered at the brand level. All continuous car characteristics are in logs and standardized, and price is in 2015 \$10,000. Footprint is vehicle length times height in square inches. Income is normalized to have zero mean and unit variance.

lead to increasing dispersion in the α_{it} distribution over time. We estimate additional specifications where we allow the parameters to vary over time and for price to enter indirect utility in logs rather than levels. Allowing preferences to vary over time provides greater flexibility in the estimation of markups, since firms will react to these changes when setting price. However, it will also imply changes in surplus due only to changes in the parameters of the utility function. We discuss the details of these alternative specifications and report results in Online Appendix B. Our estimates of markups are similar across specifications, so we perform the bulk of our analysis using the baseline specification that maintains stable-over-time parameters with clearer consumer welfare implications.

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,

$$s_{jt} = \int_i \frac{\exp(\beta_{it}\mathbf{x}_{jt} + \alpha_{it}p_{jt} + \xi_{jt})}{\exp(\gamma_t) + \sum_{l\in\mathcal{J}_t}\exp(\beta_{it}\mathbf{x}_{lt} + \alpha_{it}p_{lt} + \xi_{lt})}\, dF(i). \tag{5}$$

Shares conditional on consumer demographics can be computed by replacing the population distribution with the appropriate conditional distribution $F(i\,|\,D_{it}\in\cdot)$. 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.

IV.B. 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 in a given year. 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 markups and for counterfactual analysis. For a subset of counterfactual analysis, we parameterize marginal costs to depend on vehicle covariates including elements of $\mathbf{x}_{jt}$ and cost shifters excluded from demand, which we describe in detail in Online Appendix C.2.

Our assumption of Nash-Bertrand pricing 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 by assuming a static Nash equilibrium in prices would be misleading. We 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. (2023).

V. Estimation and Results

We estimate the model using generalized method of moments (GMM), closely following the procedures outlined by Petrin (2002) and Berry, Levinsohn, and Pakes (2004). Our estimation procedure is implemented in three steps. We briefly outline each step here and provide a full description in Online 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 micro-moments from two sources: (i) demographic information linked to car purchases from MRI and CEX and (ii) 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 of vehicle purchases for each quintile of the income distribution. For

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

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 RXR 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 equation (2) to separately estimate τ_t and γ_t from the estimated year effects.

We compute standard errors using a bootstrap procedure. We resample the microdata, including the sampled households in the CEX and MRI surveys as well as the MaritzCX survey, and reestimate 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. In the 500 bootstrap draws of the microdata, we use a nested parametric bootstrap, clustering at the make level, of the second-step estimation.

V.A. Parameter Estimates

Table IV presents the coefficient estimates for mean coefficients (column β), random coefficients (column σ), and the demographic interactions (remaining columns). The demographic estimates are intuitive and match clear patterns in the microdata. Higher-income and older consumers are less price sensitive for the relevant range of incomes. Larger family size households 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 that consumers substitute most strongly within vehicle style. The random coefficient associated with trucks is double the magnitude of the interaction of truck with a rural consumer dummy variable, suggesting that unobservable taste heterogeneity is quantitatively

8. See Online Appendix Table A.4 for a complete list of micro-moments.

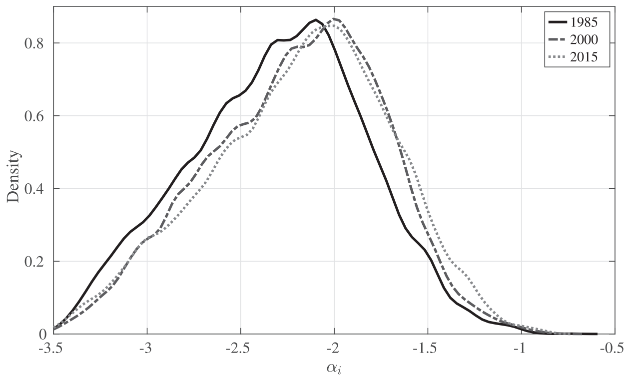


FIGURE IV

Distribution of Price Sensitivity

The plot displays smoothed kernel regression of 10,000 draws from the estimated distribution of α_i, by year, for the baseline specification with constant $\bar{\alpha}$ over time.

important. Electric vehicles also have a large estimated random coefficient.

Although we fix model parameters over time in our main specification, the distribution of price sensitivity and other tastes does change due to changes in the distribution of consumer demographics over time. For example, Figure IV presents the distribution of consumers' price sensitivity, α_i, in 1985, 2000, and 2015. Over the data period, there was a shift in the distribution toward 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 over time. To ensure that our main results on markups are not driven by our assumption of fixed parameters, we perform robustness checks by allowing more flexibility in α and other parameters. We report results on estimated markups below for these alternate specifications in the main text, and we discuss the technical details in Online Appendix B.

Our estimates of own-price elasticities for the earlier years in our sample are similar to BLP, Goldberg (1995), and Petrin (2002). The average share-weighted own-price elasticity across our entire sample is −5.06. Table V displays elasticities for the aggregate market and for a group of parent companies. Berry, Levinsohn, and Pakes (2004), on the suggestion of analysts at

TABLE V
Selected Elasticities

	Year			
	1985	1995	2005	2015
Average own-price elasticity	−4.23	−5.30	−5.78	−5.36
Market elasticity	−1.07	−1.44	−1.38	−1.29
Ford	−3.51	−4.21	−5.29	−4.75
GM	−2.64	−3.75	−4.60	−4.72
Toyota	−3.40	−5.06	−4.67	−4.40
Volkswagen	−4.15	−5.42	−5.54	−5.45
Hyundai	—	−3.43	−3.93	−4.11

Notes. "Average own-price elasticity" is the percent change in sales for a 1% increase in price, averaged across each available product (share-weighted). "Market elasticity" is the percentage change in the sales of all vehicles for a 1% increase in the price of all vehicles. Manufacturer-specific elasticities represent the percent change in sales for all cars of that manufacturer for a 1% increase in price for all cars of that manufacturer.

General Motors, calibrate their model by targeting an aggregate price elasticity of −1 for 1993. Our estimates roughly validate this assumption. Demand elasticities became more elastic from 1980 to 2005 in these categories with most of the change from 1985 to 1995. They are level or decline slightly thereafter.

V.B. 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 V displays the results of this decomposition. We find that unobservable vehicle quality is steadily increasing, roughly linearly, by a cumulative total of about \$25,000. The value of the outside option also generally increases over the time period with noticeable deviations from trend 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 new automobiles of the same observable characteristics (e.g., size, horsepower, fuel economy) but with average unobserved quality (e.g., airbags, sound system,

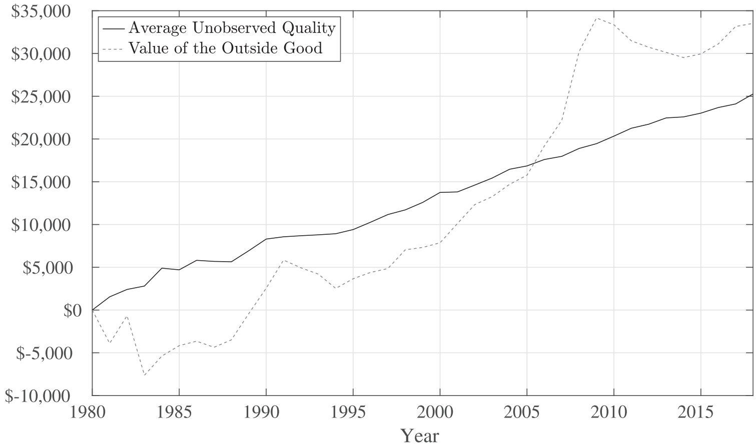


FIGURE V

Quality and Aggregate Components of Time Effects

Average unobserved quality, τ_t, and value of the outside good, γ_t, in 2015 dollars. See the text for estimation details.

durability) of 1980 versus 2018 would place a significantly higher value on the 2018 vehicle. To quantitatively assess the plausibility of the estimated 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 Online Appendix C.4. We find that the year of production dummies rise by $19,638.88 between 1992 and 2017, which is nearly 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 as improved airbag technology, body construction, rearview 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% 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 with increased 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 the 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 broader than durability, however. In addition to improvements in the attributes of used cars, the outside option is influenced by alternative transportation methods, 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 or monetary policy that may lead consumers to accelerate or postpone new car purchases.

V.C. 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 VI presents the average correlation across years for each attribute we target. These correlations suggest strong substitution patterns among vehicles with similar characteristics. As seen in the second column of Table VI, our estimated model is able to match these moments well. To emphasize the importance of observed and unobserved consumer heterogeneity in our model, we compare our fit to a series of more restrictive models. In the third column, we present the implied correlations from a model with only demographic heterogeneity

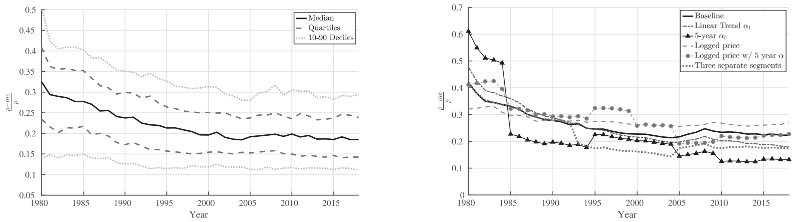
9. Although this could also be due to safer driving behavior or safer road construction, the rise of distracted driving because of mobile handsets likely pushes in the opposite direction.

TABLE VI
Attribute Correlation between First and Second Choices

	Data	Model	Alternative specifications		
			Only dem. & footprint RC	Only demographics	Logit
Van	0.720	0.727	0.048	0.008	−0.008
SUV	0.642	0.640	0.018	−0.007	−0.010
Truck	0.843	0.798	0.246	−0.013	−0.024
Footprint	0.710	0.693	0.665	−0.002	−0.018
Horsepower	0.599	0.588	0.384	0.009	−0.012
MPG	0.647	0.657	0.362	0.003	−0.013
Luxury	0.484	0.493	0.031	0.005	−0.005
Sport	0.277	0.291	0.001	−0.004	−0.004
Electric	0.373	0.192	0.002	−0.001	−0.001
Euro brand	0.336	0.353	0.018	0.000	−0.003
U.S. brand	0.479	0.472	0.121	−0.010	−0.012

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 IV, and the first column of Online Appendix Tables A.1 and A.2. The "Logit" column contains model predictions from a simple logit demand specification, with no observed or unobserved heterogeneity. 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.

and a random coefficient on footprint. This model is roughly able to match the second-choice correlation on footprint but understates the remaining second-choice correlations, even those one would expect to be highly correlated with footprint (e.g., horsepower, miles per gallon, and truck). The fourth column drops the random coefficient on footprint. Surprisingly, this model achieves essentially none of the second-choice correlations reported in the data. This is despite the fact that it matches demographic patterns well, as reported in Online Appendix Table A.4. Indeed, it is only a slightly improved fit for second choices over the logit model in the fifth column, which restricts substitution by assuming independence of irrelevant alternatives. We conclude that observable heterogeneity alone is insufficient to generate substitution patterns implied by the second-choice survey data. Online Appendix Table A.5 shows that the model matches the second-choice correlations separately in each year that we have second-choice data. Online Appendix Table A.4 displays the fit of all of the demographic moments we match.



(A) Distribution of Markups (B) Average Markups, Additional Specifications

FIGURE VI

Markups

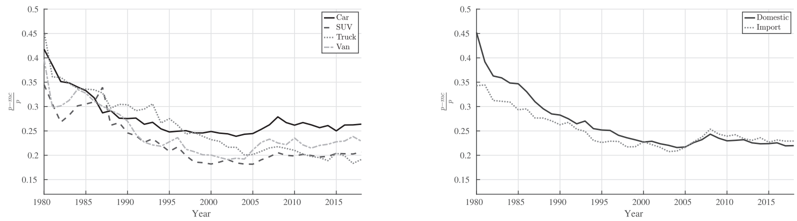
Panel A displays the median, 10th, 25th, 75th, and 90th percentiles of markups over time. Panel B displays share-weighted markups for our baseline specification and alternative specifications described in the text. Refer to Online Appendix B for a detailed description of robustness specifications.

V.D. *Markup Estimates*

We infer marginal costs of each vehicle using the first-order conditions in equation (6) at the estimated demand parameters. Online Appendix Table A.8 displays the coefficient estimates from projecting inferred marginal costs on vehicle attributes and cost shifters. Together with the observed vehicle prices and shares, we use the marginal costs to calculate vehicle markups expressed as Lerner indices ($\frac{p-mc}{p}$). Figure VI, Panel A displays the distribution of markups (median, interquartile range, and 10th–90th percentiles) over time. We estimate that the median markup is falling in our sample, from 0.325 to 0.185. Markups across the distribution also decrease.

To ensure that the functional form of our utility function is not the primary driver of the decrease in markups, we estimate alternative specifications of the model and compare the implied share-weighted markups with our baseline in Figure VI, Panel B.[10] First, we allow for a linear trend in α, the dot-dashed line, and markups have a similar trend over the sample. Second, we estimate a separate α for each five-year segment of our data, the line with triangle markers. The downward trend in markups persists. Third, we use the log of price in the utility function, shown as the light dashed line. Under this specification, the decrease in

10. For those specifications that allow for time heterogeneity in α, we add assembly country dummies as additional instruments to increase first-stage power. We discuss this instrument set in Online Appendix B. The baseline results are nearly identical when estimated with this instrument set.



(A) Markups by Vehicle Style

(B) Markups by Import Status

FIGURE VII

Markups over Time by Vehicle Style and Import Status

Share-weighted (by category) mean markups. Vehicle style is defined in the text. “Domestic” are those cars produced in the United States, regardless of brand headquarters.

share-weighted mean markups is less dramatic, 0.32 to 0.27, than in the baseline, 0.42 to 0.22. However, when we have logged price and also allow flexibility in the price parameter with separate parameters for each five-year segment (the dashed line with circles), the trend in markups looks very similar to our baseline specification. Last, we estimate the entire model for three separate time segments: 1980–1992, 1993–2004, and 2005–2018. The choice of these segments is motivated by the coverage of our survey data. The markups for this specification are the light gray dotted line, and the decrease in markups is slightly more than in the baseline, with the first 13 years having a nearly identical match. Overall, we conclude that our finding of decreasing markups is robust to alternative specifications, so we continue the analysis with our baseline specification. The details of these alternative specifications are in Online Appendix B.

In Figure VII, we display share-weighted 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, truck markups were higher than other vehicles at 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. This specific pattern is consistent with the move by Toyota and Nissan to produce trucks in the US to avoid the so-called chicken tax.[11]

11. The chicken tax is the informal name for the 25% tariff on light trucks imported into the United States. It was originally imposed during the Johnson

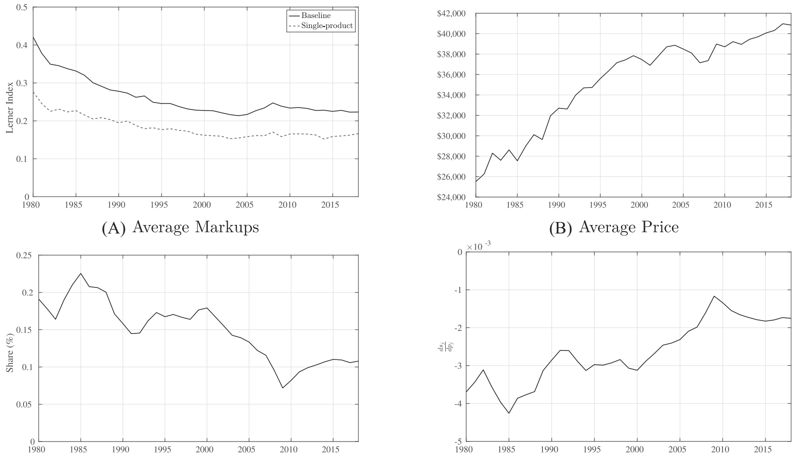
Markups for SUVs also experienced a sharp fall during the 1990s, likely due to the massive increase in competition in this segment. The number of SUVs available nearly tripled during this time, and our demand estimates imply strong within-category substitution. Turning to Figure VII, Panel B overall, imported vehicles have lower markups than domestically produced vehicles in the early decades of our sample, where our classification is based on the country of production, not the headquarters country of the product. However, domestically produced vehicles experienced a much greater fall in markups over this period, and markups are roughly equal between domestic and imported products in the final decades of our sample.

To assess sampling variability in the estimated markup trend, we use a bootstrap procedure accounting for sampling variability in the demand estimates, demographic data, and the ξ_{jt} residuals. In our baseline results, only a single product out of 9,694 has inelastic demand and all consumer price sensitivities are negative. However, in some of our bootstrap samples, some products have positive elasticities due to some consumers having positive price sensitivities. In these cases, which make up 5.6% of products over all bootstrap draws, the Nash pricing condition cannot be satisfied, and there is no inversion from observed prices to marginal costs.[12] This occurs for at least one firm in 14.2% of year and bootstrap combinations. In all bootstrap samples where the inversion is well-defined for all firms in 1980 and 2018, we find that median markups decrease over the sample period.

1. *Explaining the Evolution of Markups.* What drives the decline in markups? In the model, the exogenous forces that can change markups are changes in the ownership configuration, product entry and exit and associated changes in product characteristics, changes in the value of the outside option, and changes in consumer demographics or preferences. In our data and estimates, all of these forces are active throughout the time period.

administration to retaliate against European countries imposing a tariff on U.S. poultry.

12. One possible route to avoid this issue would be to add restrictions to increase the precision of our estimates of price sensitivity. These restrictions could take the form of additional exclusion restrictions or enforcing the supply model as part of the estimation.



(A) Average Markups

(B) Average Price

(C) Average Share

(D) Average Own-price Derivative

FIGURE VIII

Markups, Prices, and Shares

Panel A displays share-weighted mean markups for our baseline model and a model that assumes each product's price is set independently of all other products. In Panel B, average prices are in 2015 US$.

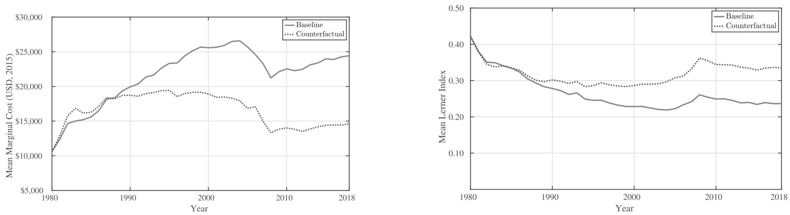
An intermediate observation to understand the estimated change in markups is that the trend is similar if we infer markups assuming single-product firms, as seen in Figure VIII, Panel A. Assuming single-product firms is a good approximation if vehicles manufactured by the same parent are not strong substitutes for each other. In the single-product firm case, the Lerner index is equal to the inverse elasticity of the product:

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

In the remaining panels of Figure VIII, we plot average prices (panel B), average market shares (C), and average derivatives of share with respect to price (D), noting that some intuition about the drivers of markups over time can be gleaned despite each being both an average and an endogenous function of the underlying preference, technology, and ownership structure primitives. This decomposition also emphasizes that price elasticities are key estimands in determining markups. For our full model, this includes both own-price elasticities as illustrated in equation (7) and Figure VIII for single-product markups and cross-price elasticities that also enter the markup equation of multiproduct firms.

During the period 1980 to 1999, when estimated markups decreased, average market shares and the average of their derivatives with respect to price are stable, while average prices increased. This combination suggests that markups decrease according to equation (7). The economic reason prices are increasing without shares decreasing and without changes in the derivative of share with respect to price is that vehicle quality is increasing. In the period 2000 to 2019, markups are stable as average market shares are decreasing, the average of their derivatives with respect to price are increasing, and average prices are roughly stable. In this latter period, although quality is still increasing steadily, the outside option also experiences substantial growth, which can explain the flattened average price trend and offsetting the decline in average shares and increase in the average of their derivative with respect to price. Under the logic of equation (7), this combination leads to flat markups.

To study which primitive factors explain the estimated decline in markups, we turn to counterfactual simulations. To consider the impact of concentration, the first counterfactual we perform adjusts the ownership matrix in each year to remove the impact of the growth of competition from foreign brands since 1980. To consider the effect of product proliferation, our second counterfactual holds the number of products fixed over time at the level of 1980. These counterfactuals are described in full in Section VI.B as Mechanisms 1 and 2. These changes to primitives do not eliminate the decrease in markups we observed in our baseline results. We display the results in Online Appendix Figure XVIII. Next we simulate a counterfactual where the observable characteristics of vehicles in each year are scaled down to match the distribution of characteristics from 1980. Specifically, if a vehicle is in a certain percentile of a characteristic in a given year, we assign the same percentile from the 1980 distribution of that characteristic. As a result of this change, which shifts the distribution of products toward lighter, lower-horsepower vehicles, the increase in marginal costs over time estimated by our model is effectively eliminated, as shown in Figure IX, Panel A. The reason marginal costs are flat despite an estimated downward technological trend is that there is an offsetting upward time trend in the RXR, see Online Appendix Figure A.8. Other primitives, like



(A) Marginal Cost: Baseline vs. Counterfactual

(B) Markups: Baseline vs. Counterfactual

FIGURE IX

Counterfactual Markups, 1980 Distribution of Characteristics

For each vehicle in each year, we assign the same percentile from the 1980 distribution of each characteristic, recompute marginal costs, which are plotted in Panel A, and recompute the pricing equilibrium and share-weighted mean markups which are plotted in Panel B.

the number of products and the market structure, are allowed to evolve as they do in the data. This counterfactual, which effectively eliminates the growth in observed product quality, does significantly reduce the fall in markups, as shown in Figure IX, Panel B. The main takeaway of this exercise is that a major driver of the decline in markups is that increasing observable quality of vehicles results in increasing marginal costs that are less than fully passed through to consumer prices.

The importance of vehicle quality in driving markup trends highlights the fact that markups are not conceptually attractive proxies for welfare when the product set is changing.[13] This fact motivates our focus on the model's measures of welfare and surplus over time to assess industry performance in Section VI.

V.E. *Robustness to Conduct Assumption*

In this section, we compare markup estimates under alternative assumptions of conduct. To summarize the results, while there is a disparity in the level of markups, these alternatives all point toward declining markups over the sample period, as

13. For a simple example of when markups can be misleading, consider a monopolist facing logit demand 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 that markups rise. However, since $\frac{d(\delta-\alpha p)}{d\delta} = 1 - s > 0$ consumer surplus also increases.

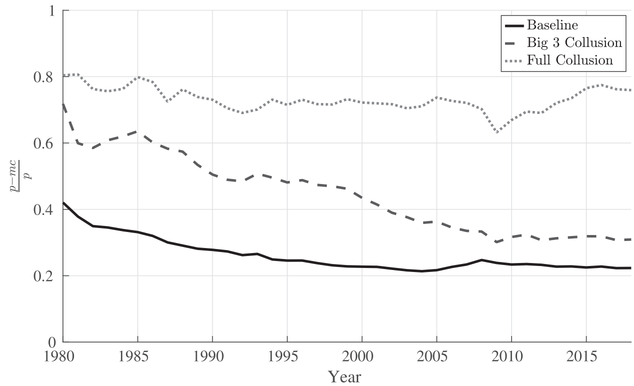


FIGURE X

Markups: Alternative Conduct Assumptions

Estimated share-weighted mean markups for Nash-Bertrand pricing by parent companies (Baseline), the Big Three 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 (Full Collusion).

in the base case of Nash-Bertrand pricing. In the first case, we assume the Big Three U.S. auto manufacturers (GM, Ford, and Chrysler) collude on prices for our entire sample.[14] 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 Three firms over time. Notably, markups at the end of the sample under the assumption that the Big Three collude are lower than the Nash-Bertrand markups at the start of the sample. Therefore, under the assumption that the Big Three 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, markups are much higher. However, there is still a decrease in markups over the time period.

Figure X establishes that markups decline over time under a variety of constant conduct assumptions. However, it is possi-

14. For Chrysler, we follow the ownership from Chrysler to Daimler to Cerebus private equity firm, then to Fiat, and assume that 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 VII
AVERAGE MARKUPS WITH DIFFERENT CARTEL ASSUMPTIONS

	Mean markup	HHI
1980 baseline	0.42	2,661
2018 baseline	0.22	1,132
2018 hypothetical cartel membership		
GM + Ford + Toyota	0.26	2,546
Top 3 + Fiat	0.35	3,724
Top 4 + Honda	0.39	4,819
Top 5 + Nissan	0.46	6,000

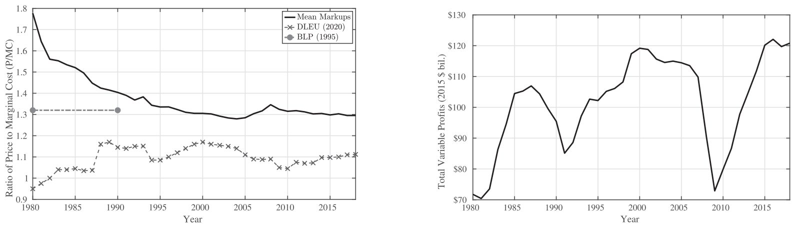
Note. Computed share-weighted mean markups and HHI with simulated collusion in 2018 for various manufacturer cartels. Fiat is the parent company of Chrysler in 2018.

ble 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 noncollusive 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 VII. One change in conduct from Nash-Bertrand that would produce estimated increases in markups would involve a cartel of the six largest parent companies (Top Five + Nissan) forming during our sample. 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. Indeed, given the greater concentration among U.S. automakers, it seems more likely that the 1970s and earlier periods would be subject to coordinated pricing decisions.[15]

V.F. *Comparison to the Production-Based Approach*

De Loecker, Eeckhout, and Unger (2020) (DLEU) use financial data from Compustat to estimate markups. This approach

15. Bresnahan (1987) investigates a potential breakdown in collusion among U.S. automakers in 1955. More recently, in 2013 the Department of Justice secured convictions of nine automobile parts suppliers fixing prices of sales to U.S. auto manufacturers plants (see https://www.justice.gov/opa/pr/nine-automobile-parts-manufacturers-and-two-executives-agree-plead-guilty-fixing-prices), suggesting that the DOJ would be attuned to coordination in the auto industry itself. The effect of this collusive ring raising manufacturers' costs of inputs would be captured in our estimates of marginal cost.



(A) Price over Marginal Cost

(B) Total Variable Profits

FIGURE XI

Comparison to De Loecker, Eeckhout, and Unger (2020)

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, Eeckhout, and Unger (2020), and the average estimate across 1971–1990 from Berry, Levinsohn, and Pakes (1995). Panel B displays our estimate of total variable profits, quantity sold multiplied by margins, summed across all products.

uses a model of firm production and data on input expenditures and output revenue to estimate price over marginal cost ratios.[16] In their baseline results, they estimate an increase in the sales-weighted average price to marginal cost ratio (across all sectors) from 1.21 to 1.61 from 1980 to 2016. In addition to aggregate results, DLEU report estimates for specific industries, including the U.S. auto industry. Figure XI, Panel A displays the time series of average price to marginal cost ratio from their work together with our own measure. We also include an estimate from Berry, Levinsohn, and Pakes (1995), which reports an average price to marginal cost ratio from 1971–1990. Both the level and trends in the price to marginal cost ratio differ from the estimates we derive, though both series are relatively flat from 1995 onward. In the right panel, we plot our estimates for total variable profits, which is the sum of price minus marginal cost multiplied by quantity sold over models in a year. Quantity thus enters directly into the right panel but does not enter directly in our estimates in the left panel. Our estimates for total variable profits share some patterns with the DLEU estimates for markups, including an increase in the 1980s, a dip and recovery in the 1990s, and a dip and recovery around the Great Recession.

16. For purposes of comparison, this section reports markups as the price to marginal cost ratio $\frac{p}{c}$ rather than the Lerner index, $\frac{p-c}{p}$.

The two markup estimates rely on different underlying data and nonnested sets of assumptions. The approach for our estimates relies on a credible demand system and an assumption of static Nash pricing conduct by the manufacturers.[17] The DLEU approach relies on an assumption of cost minimization with respect to a fully flexible input and credible production function estimation to measure the elasticity of output with respect to the flexible input.

There are a number of potential issues in implementing the production approach that may lead to inaccurate estimates in this context. First, if the input used to obtain marginal costs is not freely chosen by the firm (e.g., if it contains any fixed rather than variable costs), the static first-order condition at the heart of the approach does not apply. The flexible input employed in DLEU is cost of goods sold (COGS) reported in Compustat at the firm-year level. In the context of auto manufacturing, COGS includes some marginal costs, such as the additional material or labor costs associated with producing additional vehicles, but it also includes, by generally accepted accounting principles, fixed overhead associated with manufacturing. That is, manufacturers are required to allocate fixed overhead costs as part of COGS. For example, the Ford Motor Company Annual Report for 1994 states: "Further, because the automotive industry is capital intensive, it operates with a relatively high percentage of fixed costs which can result in large changes in earnings with relatively small changes in unit volume" (Ford Motor Company 1995). However, at the same time, Compustat records Ford as reporting all of its operating expenses in this year as COGS. In this sense, COGS contains capital expenditures that the firms identify as fixed costs and thus may not satisfy the requirements as a flexible input.[18] In practice, including fixed costs in the flexible input can lead to variation over time in the estimated markups even when the true price over marginal cost is fixed, simply due to fluctuating quantities. Being driven by quantity sold rather than the true price to marginal-cost ratio is a potential reason the DLEU series shares some patterns with our estimates of total variable profits over time in Figure XI, Panel B.

17. Although, as we noted already, the downward trend in markups is robust to a variety of conduct assumptions.

18. Relatedly, Traina (2018), Raval (2023), and Demirer (2022) examine how markup estimation can be sensitive to the choice of flexible-input and related functional-form assumptions.

A second set of challenges are due to the estimation of output elasticities. Ideally, output elasticities would be estimated as part of a production function relating quantities of output to quantities of input accounting for endogenous input choices on the part of firms. There are three practical challenges with estimating output elasticities using Compustat data that may contribute to differences in the estimated series. First, Compustat reports total revenues at the firm-year level, whereas a traditional output elasticity would be estimated using quantity instead of revenue (Bond et al. 2021). Second, observing revenue at the firm-year level leads to abstracting away from the multiproduct nature of production, with unknown consequences for the interpretation of the resulting output elasticity used to estimate markups. Third, there is the question of allowing for cross-firm heterogeneity in output elasticities, which can be challenging since Compustat contains only public firms. To address this, DLEU pool firms in the same two-digit NAICS code to estimate output elasticities which pools auto manufacturers in NAICS code 33 with a wide range of manufacturing segments, including computer manufacturing, ship building, furniture manufacturing, and many others. Using the Annual Survey of Manufacturers, Foster, Haltiwanger, and Tuttle (2022) estimate output elasticities allowing for flexibility across firms in the same industry and finds, in some specifications, decreasing average manufacturing markups for the period 1977 to 2012.

Finally, differences in the data sample may account for discrepancies between the two series. The demand approach uses price and quantity data of products available in a given market—the U.S. new car market in our case. The production approach is applied to a collection of firms assumed to have a similar production technology with no explicit assumption on conduct. In the case of the Compustat data used by DLEU, the firms included are primarily those publicly listed on U.S. stock exchanges. Consequently, the data do not include some important auto manufacturers who sell in the United States (e.g., Volkswagen, BMW, Hyundai-Kia, Nissan, Mazda, and Mitsubishi) in certain years. For example, Nissan enters the Compustat data in 1989, and Volkswagen enters in 2001, even though both were selling in the U.S. market before these dates. BMW, Hyundai-Kia, Mazda, and Mitsubishi never appear in the data set. Moreover, Compustat includes additional revenue streams outside of automobile manufacturing such as any vertically integrated parts manufacturing, consumer financing operations, or manufacturing of other products. Finally, the revenue information in Compustat will include sales of vehicles outside of the U.S. market, which may have very different markups than autos sold inside the U.S. market.

Census or industry-specific production data sets can alleviate some of these concerns. For example, the U.S. Census of Manufacturers includes inputs, such as materials and energy, which are arguably closer to flexible. It also contains quantity data for select industries. However, only the Census of Manufacturers (as opposed to other parts of the Economic Census) is well suited to estimating output elasticities, and even for manufacturing there is little information on multiproduct production.[19] Moreover, such data would contain information only on products produced in the United States. Compared to our data set, this excludes the substantial number of imported automobiles and incorrectly includes automobiles that are exported.

Focusing on the period 1980 to 1987, where the two estimates behave most differently, one can reconcile the differing patterns as follows. This period saw an increase in manufacturing costs due to rising labor costs, as union contracts were indexed to inflation which exceeded 10% per year in the early 1980s, and vehicles were being made with higher fuel efficiency at extra cost in response to the 1970s oil crises. Second, the economy went through two recessions during 1980–1984. Third, imports from Japan were capturing more market share. In response to these patterns, the U.S. manufacturers engaged in restructuring and layoffs. The DLEU measures more closely match the overall profitability of the firm, as COGS includes both marginal and fixed costs. The increase in profitability is the fruit of these restructuring efforts. Our estimates, on the other hand, reflect rising marginal costs of production that are not able to be fully passed through to consumer prices, resulting in decreasing markups. Part of the difference is also due to the entry of Daimler into the Compustat data underlying the DLEU estimates in 1988. Daimler, which also operated in aerospace and other segments, had a significantly larger revenue to COGS ratio than the other

19. Similar industry-level data sets may sometimes be available for services. For example, Bet (2021) reports production-based estimates for the domestic airline industry using detailed data from the Bureau of Transportation Statistics and estimates different levels and time series behavior for markups than those reported for airlines in DLEU.

automobile manufacturers in Compustat and receives significant weight in the share-weighted markup due to its worldwide revenues.

Given the difficulties with estimating markups via the production approach in practice, we believe the approach of estimating markups using detailed demand data and conduct assumptions is a useful alternative. This approach does have the downside of requiring detailed industry-specific data sets and tailored modeling to each market under study. While resource intensive, this research is feasible. Indeed, in some cases, the two approaches may agree. De Loecker and Scott (2016) examine production- and demand-based estimates for beer and find the two approaches produce plausibly similar markup estimates. An important advantage of the demand-side approach is that it provides direct measures of consumer surplus that are not available without an estimated demand system and accounts for changing product quality over time. For the remainder of the article, we use our estimates to go beyond markups and analyze the welfare trends of the U.S. automobile industry.

VI. 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.

VI.A. 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. Although 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. Both of these cases will affect the standard consumer surplus measure, even when the quality of automobiles and their prices are held fixed. We construct a measure of consumer surplus that captures the attractiveness of the choice set and is straightforward to compare across years. For each year, instead of using the value of the outside option associated with that year, we average the compensating differential over all of the 39 (1980–2018) estimated values of outside options.

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

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

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,

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

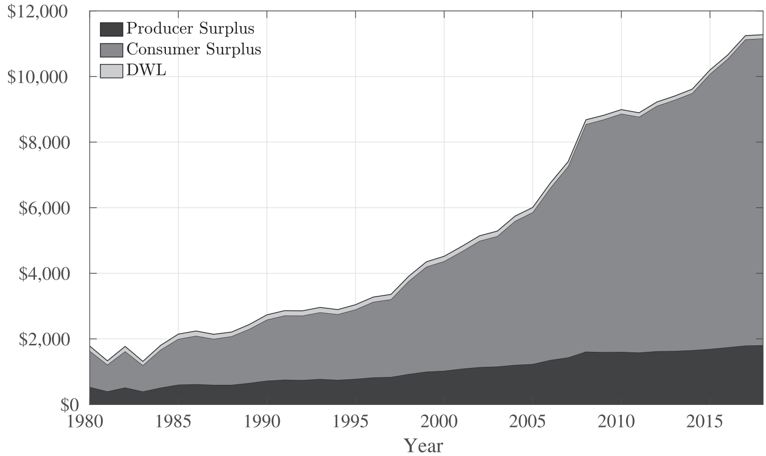


FIGURE XII

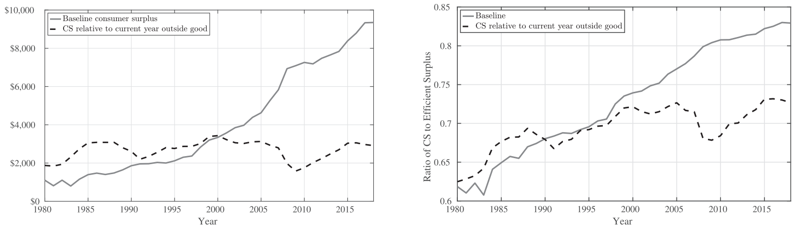
Consumer Surplus, Producer Surplus, and Deadweight Loss

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

We can compute producer surplus and deadweight loss measures analogously.

In Figure XII 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. Surplus is displayed as per U.S. household. Total surplus rises by roughly \$9,000 per household, from around a little less than \$2,000 to roughly \$11,000. 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 decrease in prices comes with the entry of the second and third firms in 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.[20]

20. 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



(A) Consumer Surplus Comparison (B) CS as a Share of Total Available Surplus

FIGURE XIII

Consumer Surplus Comparison

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 using both approachs presented in Panel A, where efficient surplus is computed as consumer surplus when prices equal estimated marginal costs of production, vehicle by vehicle.

The more common measurement of consumer surplus in the industrial organization literature simply compares the value of the choice set to the current year's estimated value of the outside option, or $CS_t(\gamma_t)$ in our notation. This is a more static approach, which may be appropriate when the researcher does not have a long time series with a drastically changing outside option. Figure XIII, Panel A displays both measures of consumer surplus. Under the traditional measure, consumer surplus is relatively flat over the period with marked troughs in the early 1980s, early 1990s, and 2009, corresponding to the three major economic downturns in our sample period. Clearly, this measure confounds the value of the set of available products with the value of the outside option when comparing across years. The difference between these panels is intuitive given the significant changes in our estimates of the value of the outside good over time, as shown in Figure V. Figure XIII, Panel B plots the share of consumer surplus of total efficient surplus. We do this for our baseline measure of consumer surplus, as well as for the traditional measure. In both cases, consumers' share of available surplus is increasing from 1980 to 2018. For our baseline measure, consumers' share of surplus rises from 0.62 to 0.82.

companies. On average, of a vehicle's 5 closest substitutes, 3.8 are produced by rival manufacturers, and 7.8 of the top 10 substitutes are rivals.

VI.B. 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, and 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 the main drivers of consumer surplus growth.

1. *Mechanism 1: Increased Competitive Pressure from Foreign Brands.* It is possible that the increase in foreign brands competing in the United States led to downward pressure on prices that benefited consumers.[21] To understand this mechanism, we simulate an alternative scenario where we assume that all vehicles sold by foreign brands in our data are instead owned by the Big Three U.S. car manufacturers (GM, 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 Three firms and recompute the pricing equilibrium. We do this 10 times and take an average of the outcomes across the random assignments. Chrysler experiences ownership changes, so we track the ultimate owner of the Chrysler brand and treat that company as a Big Three firm. Although this exercise captures the effect of competition on prices, it holds fixed product design or quality and productivity. It is possible that improvements in product quality or marginal

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

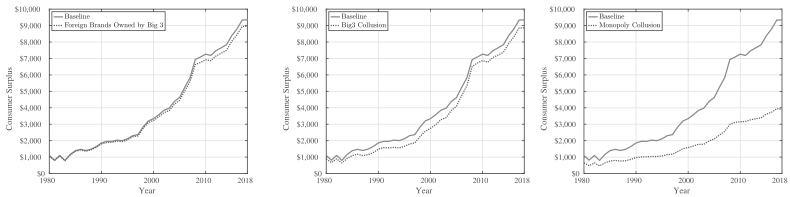


FIGURE XIV

Consumer Surplus: Alternative Product Ownership

The vertical axis represents consumer surplus per U.S. household in 2015 dollars. In the left panel, we simulate the market equilibrium if all vehicles produced by foreign brands were owned by the Big Three U.S. car manufacturers (randomly assigning new ownership). In the middle panel, we simulate market equilibrium if the Big Three jointly set prices. In the right panel, we simulate market equilibrium if all firms jointly set prices.

costs may ultimately be attributable to increased pressure from foreign competition.

The results, in terms of consumer surplus, are presented in the left panel of Figure XIV. Throughout this section, the solid line in the 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 in clusters of similar products.

We benchmark the result against two alternatives to emphasize this point. In the middle panel, we plot a counterfactual where the Big Three 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 that eliminates foreign-brand competition does not achieve this.

2. *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 are

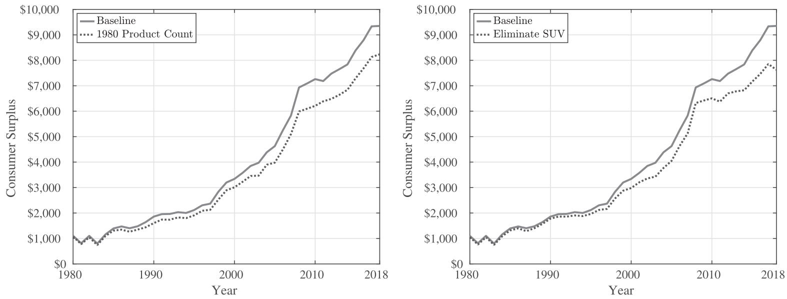


FIGURE XV

Consumer Welfare, Product Proliferation

The vertical axis represents consumer surplus per U.S. household in 2015 dollars. In the left panel, we simulate the market equilibrium if we eliminate (randomly) products in every year so that the number of products in the choice set is the same as in 1980. In the right panel, we eliminate all SUVs from our sample and simulate the market equilibrium.

heterogeneous and thus benefit from variety, all else equal. 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 of 165 available products.[22] The results are presented in the left panel of Figure XV. 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. The intuition behind this result is that even though many products are eliminated from the choice set, consumers can substitute toward similar products. The rich substitution patterns of our demand system are important to capturing this effect. Indeed, under the logit model—which assumes symmetric unobserved product differentiation (Ackerberg and Rysman 2005)—the increase in welfare over the 1980–2018 period is roughly five times larger than under our model, largely as a result of product proliferation.

22. In practice, we randomly select 165 products to be available each year. We do this procedure 10 times and take an average of the outcome.

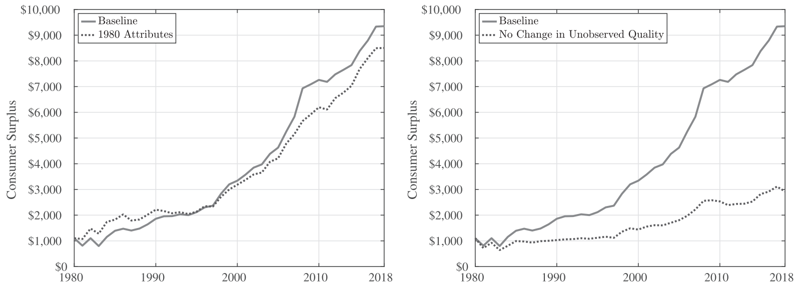


FIGURE XVI

Consumer Welfare, Changes in Attributes

The vertical axis represents consumer surplus per U.S. household in 2015 dollars. In the left panel, we simulate the market equilibrium if in each year we rescale the distribution of footprint, horsepower, MPG, curb weight, and height, to match the 1980 distribution. In the right panel we eliminate the improvements to average unobserved quality, ξ_{jt} over time.

Another major development related to product proliferation is the rise in the the number of SUVs available to consumers, as we documented in Figure II, Panel D. SUVs today represent a 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 SUVs to generate large consumer surplus gains. The right panel of Figure XV displays 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. Although consumer surplus is lower than in the baseline, the difference is modest and only explains a small portion of the rise in consumer surplus between 1980 and 2018.

3. *Mechanism 3: Changing Product Attributes.* We turn to changes in product characteristics. A notable trend in the industry has been the general growth in car characteristics such as size and horsepower, as we documented in Figure III. To see how these improvements affected consumer surplus, we scale the distribution of horsepower, MPG, footprint, height, and curb weight 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 left panel of Figure XVI. They indicate a modest impact on consumer surplus from this source.

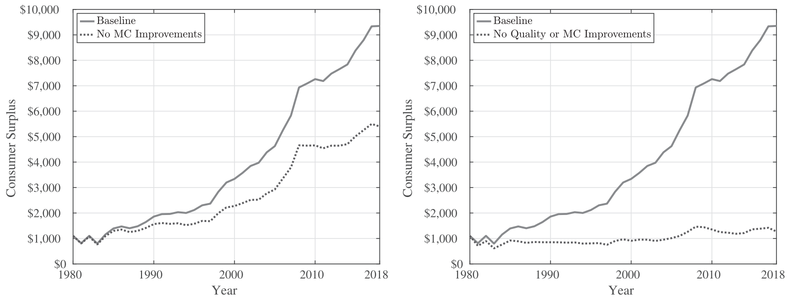


FIGURE XVII

Consumer Welfare, Changes in Production Efficiency

The vertical axis represents consumer surplus per U.S. household in 2015 dollars. In the left panel, we simulate the market equilibrium if, in each year, we eliminate the production efficiency trend estimated in Online Appendix Table A.8. In the right panel, we eliminate both the changes in production efficiency (left panel) and unobserved quality (right panel of Figure XVI).

In addition to improvements in observable characteristics, we documented a steady rise in unobservable quality (see Figure V). In the right panel of Figure XVI, we simulate a counterfactual where the unobservable mean vehicle quality is fixed at 1980 levels. Specifically, since the rise in ξ is captured by the quality adjustment term τ in equation (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 airbags and rear view cameras, reliability improvements, and improved electronics like Bluetooth audio and navigation.

4. *Mechanism 4: Decreasing Costs.* As we report in Online Appendix C.2, our results indicate that the marginal costs of producing a car with fixed characteristics has experienced a steady decline of 1.4% a year over the sample period. To investigate the welfare implications of these technological improvements in production, the left panel of Figure XVII eliminates the downward trend in marginal costs. We find that welfare increases by about half as much as in the baseline. Thus, technological progress in production is also a significant driver of the measured increase in consumer surplus.

Finally, in the right panel of Figure XVII, we combine the improvement in marginal costs and the improvement in vehicle quality (from the right panel of Figure XVI) and simulate a world where neither the unobservable product quality increases nor marginal costs fall. This combination almost entirely eliminates the measured increase in consumer surplus.

VII. Conclusion

Antitrust policy has come under scrutiny in the United States in recent years. Critics argue that weak antitrust enforcement from the 1980s onward has led to an increasingly tight grip of large firms over product markets to the detriment of consumers. In this article, we focus on the new automobile market over nearly 40 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 production 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 safety, reliability, comfort, and improved electronics. We find that competition was healthy enough that benefits from these improvements mostly accrued 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 consider specific models 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 modeling of the joint dynamics of new and used cars could lead to more precise measurements of consumer welfare.

Most important, 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 for validating 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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Supplementary Material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

Data Availability

The data and code underlying this article are available in the Harvard Dataverse, https://doi.org/10.7910/DVN/CZGOKP (Grieco, Murry, and Yurukoglu 2023).

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