The Evolution of Market Power in the US Auto Industry

Paul L. E. Grieco  Charles Murry  Ali Yurukoglu
Penn State  Boston College  Stanford GSB
Research Questions

How did market power and consumer welfare evolve in the US auto industry from 1980-2018?

How is this related to changes in
- market structure,
- import penetration,
- product proliferation and differentiation,
- characteristics and marginal costs?
Motivation

Now famous result: economy-wide markups are rising. [DLEU (2020)]

Generated a lot of follow-on research on concentration and competition policy.

Lots of criticism about empirical methods.

Our Contribution
Provide detailed industry study of market power and industry efficiency using canonical IO methods.
Approach

1. Estimate rich product-level demand system.
   - Identify heterogeneity using microdata to measure substitution patterns.
   - Cost shifter IV to measure price sensitivity: real exchange rates.

   **Outcome:** elasticities & consumer welfare.

2. Assume firm conduct to infer marginal costs.
   - Static Nash-Bertrand by manufacturers.

   **Outcome:** marginal costs, markups, total surplus.
Main Findings I

1. Prices rise. Bad?

![Graph showing mean price and IQR over years from 1980 to 2015]
Main Findings I

1. Prices rise. Bad?

2. But markups decrease. Good?
Main Findings I

1. Prices rise. Bad?

2. But markups decrease. Good?

1 + 2 → Cost rising faster than prices. Bad?
Contrast to DLEU (2020)

Ratio of Price to Marginal Cost (P/MC)

Year

Mean Markups

DLEU (2020)

BLP (1995) Estimate
Why do we care about long-term trends in markups?

Fixed choice set intuition:

\[
\text{markups } \uparrow, \quad \Rightarrow \quad \text{consumer welfare } \downarrow.
\]

When products are change this no longer holds.

Comparing markups over time has similar pitfalls as comparing markups/prices/etc across industries [Demsetz, 1973].
Main Findings II

So we look at **Consumer Surplus** directly:
Main Findings III

Why does Consumer Surplus increase?

Major factors:
- Product quality (e.g., design, air conditioning, electronics,...).
- Production improvements that lower marginal cost.

Moderate factors:
- Number of products.
- Introduction of SUVs.

Negligible factors:
- Less concentrated market structure (rise of imports);
- Trends in size, weight, horsepower, mpg.
Data and Industry Trends
Markets and Products

**Market**

**Product**
Vehicle make/model “owned” by a manufacturer.
Ex: Audi A5 in 2016 from Volkswagen AG.
Data Construction (1/2)

**Market:** Entire USA, yearly for 1980-2018.

**Source 1. “Macrodata”** from Wards Auto Yearbooks.
- Model-level sales, MSRP and characteristics.

**Source 2. “Microdata:” Demographics**
- Survey respondents report car make/model purchased, price, and demographics.

**Source 3. “Microdata:” Second-choices**
- Survey respondents report alternative cars considered.

**Additional Sources**
Production location, model redesigns, EV characteristics, misc missing information.
Data Construction (2/2)

We aggregate “trims” to “models” by taking the median characteristics of each model across trims.

Issues to consider
- Sales year v. model year issues.
- Within year entry and exit of models.
Aggregate Trends

1. Rising prices (as noted earlier).

2. Decreasing concentration.

3. Increasing car quality in many dimensions.
Fewer firms, but lower HHI,
Product Portfolios of Manufacturers

Ownership of Products

1985

1995

2005

2015

“Big 3”
Power ↑ with same fuel efficiency, Knittel (2011).
Vehicles are getting bigger and heavier…
Other quality improvements...
Empirical Strategy
Model Overview

**Demand:** Differentiated product discrete choice.
- Observed and unobserved taste heterogeneity → flexible product substitution.
- Price variation from real exchange rate of assembly country. (Cost shifter IV.)

**Supply:** Multiproduct Nash-Bertrand equilibrium
- “Back out” implied marginal costs.
- Conduct assumption not imposed during demand estimation (incl. cost, not competition-based IV).
Model Specification (very brief)

**Demand**
Each year \((t)\), households \((i)\) make a discrete choice over the available vehicle models \((j)\) and outside option.

\[
u_{ij} = \beta_i x_{jt} + \alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt}.
\]

**Supply**
Each year: static, simultaneous, Nash Eq. in prices.

Price FOC:
\[
q_j + \sum_{k \in J_t^m} (p_j - c_j) \frac{\partial q_j}{\partial p_k} = 0
\]
Identification Overview

1. Price elasticity: real exchange rate IV.

2. Observed heterogeneity: CPS/MRI microdata moments, e.g.,

\[ E[\text{footprint}_{j(i)}|\text{family size}_i] \]

3. Unobserved heterogeneity: Marritz second choice moments, e.g,

\[ \text{Corr}[\text{footprint}_{j(i,1)}, \text{footprint}_{j(i,2)}] \]

where footprint\(_{j(i,c)}\) is the characteristic of consumer \(i\)'s \(c\)th choice product.
**IV for Price: Real Exchange Rate**

\[
RXR_{jt} = \frac{PPP_{jt}}{e_{jt}} = \frac{\text{ratio of price levels}}{\text{nominal exchange rate}}
\]

lagged \(pl_{-con}\) from the Penn World Table.

\(RXR_{jt}\) varies when
- PPP changes (e.g., local labor costs),
- nominal exchange rates change (used in Goldberg and Verboven, 2001)
- BLP (1999) uses \(e\) and a measure of local wages.

**Examples**
- If wages rise in Japan then cost in yen goes up, RXR goes up, and Toyota should raise prices in the US.
- If yen depreciates relative to dollar (\(e\) goes up) so one dollar buys more yen, then RXR goes down, and Toyota should lower prices in the US.
- After NAFTA, Ford starts outsourcing Ford Ranger/F-150 production to Mexico.

**Positive relationship between RXR and consumer prices in US.**
## IV Logit Results / First Stage

<table>
<thead>
<tr>
<th></th>
<th>First Stage</th>
<th>Reduced Form</th>
<th>Logit Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real XR*</td>
<td>4.867 (0.991)</td>
<td>-0.993 (0.285)</td>
<td>OLS</td>
</tr>
<tr>
<td>Price</td>
<td></td>
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<td>-0.042 (0.005)</td>
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<tr>
<td>Characteristics</td>
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<td>yes</td>
<td>yes</td>
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<tr>
<td>Make Dummies</td>
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<td>yes</td>
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<td>Year Dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
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<td>N</td>
<td>9611</td>
<td>9611</td>
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<tr>
<td>Mean Own Price Elas.</td>
<td>–</td>
<td>–</td>
<td>-1.50</td>
</tr>
<tr>
<td>*Implied XR Pass-through</td>
<td>0.146</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>First Stage F-Stat:</td>
<td>24.13</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Standard errors clustered by make.
Micromoments

Observed Heterogeneity

Price X Income
\[ E[p_{ij^*} \mid Inc_i^{Qx}] - E[p_{ij^*} \mid Inc_i^{Q1}] \]

Price X Age
\[ E[p_{ij^*} \mid Age_i^{60+}] - E[p_{ij^*} \mid Age_i^{<30}] \]

Car Size X Family Size
\[ E[CarSize_{ij^*} \mid FS_{i}^{5+}] - E[CarSize_{ij^*} \mid FS_{i}^{1}] \]
\[ E[CarSize_{ij^*} \mid FS_{i}^{3-4}] - E[CarSize_{ij^*} \mid FS_{i}^{1}] \]

Unobserved Heterogeneity

Corr(\(x_j(i,1), x_j(i,2)\))
for \(x = \text{Van, Truck, SUV, HP, Footprint, MP\$, Luxury, Sport, EV, USBrand, EuroBrand}\)
Results
## Utility Estimates

<table>
<thead>
<tr>
<th></th>
<th>( \beta )</th>
<th>( \sigma )</th>
<th>Income</th>
<th>Inc.(^2)</th>
<th>Age</th>
<th>Rural</th>
<th>FS 2</th>
<th>FS 3-4</th>
<th>FS 5+</th>
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<td>0.094</td>
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<tr>
<td></td>
<td>(0.081)</td>
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<td>(0.008)</td>
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<td>(0.102)</td>
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<td>Van</td>
<td>-7.292</td>
<td>5.348</td>
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<td>1.668</td>
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<td>(0.148)</td>
<td>(0.157)</td>
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<td>SUV</td>
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<td>(0.049)</td>
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<td>Truck</td>
<td>-7.533</td>
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<td>–</td>
<td>3.009</td>
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<td>(0.286)</td>
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<td>(0.308)</td>
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<td>Footprint</td>
<td>0.517</td>
<td>1.884</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.483</td>
<td>0.463</td>
<td>0.645</td>
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<td>(0.372)</td>
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<td>(0.077)</td>
<td>(0.072)</td>
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<td>Horsepower</td>
<td>1.094</td>
<td>1.249</td>
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<td></td>
<td>(0.45)</td>
<td>(0.086)</td>
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<td>Miles/Gal.</td>
<td>-0.945</td>
<td>1.636</td>
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<tr>
<td>Sport</td>
<td>-3.066</td>
<td>2.62</td>
<td>–</td>
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<td>–</td>
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<td>(0.067)</td>
<td>(0.056)</td>
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<td>Electric</td>
<td>-5.342</td>
<td>3.835</td>
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<td>–</td>
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<td></td>
<td>(0.128)</td>
<td>(0.084)</td>
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<tr>
<td>EuroBrand</td>
<td>–</td>
<td>1.923</td>
<td>–</td>
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<td>(0.029)</td>
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<td>USBrand</td>
<td>–</td>
<td>2.14</td>
<td>–</td>
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<td>(0.032)</td>
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<tr>
<td>Constant</td>
<td>-3.164</td>
<td>0.362</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<tr>
<td></td>
<td>(4.311)</td>
<td>(0.031)</td>
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</table>

Other linear parameters: Brand dummies, Year dummies, years since redesign.
## Elasticities and Substitution

### Price Elasticities by Income over Time

<table>
<thead>
<tr>
<th>Year</th>
<th>Income Quintile</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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<tbody>
<tr>
<td>1980</td>
<td></td>
<td>-5.96</td>
<td>-5.78</td>
<td>-5.49</td>
<td>-5.13</td>
<td>-4.30</td>
</tr>
</tbody>
</table>

### Correlation b/w 1st & 2nd Choice, 2015

<table>
<thead>
<tr>
<th>Name</th>
<th>Data</th>
<th>Model Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Van</td>
<td>0.71</td>
<td>0.71</td>
</tr>
<tr>
<td>SUV</td>
<td>0.64</td>
<td>0.64</td>
</tr>
<tr>
<td>Truck</td>
<td>0.84</td>
<td>0.80</td>
</tr>
<tr>
<td>Footprint</td>
<td>0.71</td>
<td>0.69</td>
</tr>
<tr>
<td>Horsepower</td>
<td>0.60</td>
<td>0.59</td>
</tr>
<tr>
<td>MPG</td>
<td>0.65</td>
<td>0.65</td>
</tr>
<tr>
<td>Luxury</td>
<td>0.48</td>
<td>0.49</td>
</tr>
<tr>
<td>Sport</td>
<td>0.28</td>
<td>0.28</td>
</tr>
<tr>
<td>Electric</td>
<td>0.37</td>
<td>0.19</td>
</tr>
<tr>
<td>Euro. Brand</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>US Brand</td>
<td>0.48</td>
<td>0.47</td>
</tr>
</tbody>
</table>
Markups Over Time

\[(\text{Price} - \text{Marg. Cost}) / \text{Price}\]

- Domestic
- Import
- Car
- SUV
- Truck
- Van
Why do Markups fall?

Single product Bertrand pricing:

\[
\text{Markups} = \frac{1}{\text{elas}} = \frac{s}{p} \times \frac{1}{\frac{ds}{dp}}
\]

\(\frac{ds}{dp}\): Relatively stable over time.

shares: Stable.

prices: Increasing substantially \(\implies\) higher quality.
Prices rise $\implies$ markups fall

![Graph showing the relationship between prices and markups from 1980 to 2015. The graph includes four lines representing Baseline Markups, Single-product Markups, 1/Price, and another line labeled p-me. The y-axis represents the values of these variables, and the x-axis represents the years from 1980 to 2015. The graph illustrates a downward trend in markups as prices rise.](image-url)
Why care about markups?

If products are changing substantially, **markup** is not a conceptually attractive notion of industry efficiency.
Welfare Calculation

Welfare is calculated relative to outside good.

Year dummy captures:
- average product quality change over time;
- aggregate fluctuations in desirability of outside good.

We want welfare trends that account for car quality, but not recessions or other changes in “outside good”.
Our strategy: Leverage continuing products

Decompose year effects into mean quality and macro shocks:
- Assume mean utility of continuing projects does not change between $t$ and $t + 1$.
- Decline in $E[\xi_t|\text{continuing}]$ represents shift in mean car quality between $t$ and $t + 1$.
- Remainder of year effect ascribed to aggregate fluctuations in outside good.

To calculate welfare integrate over aggregate component (calculating counterfactual equilibrium) to remove its impact.
Quality Adjustment

Year

Quality Adjustment
Aggregate Component
Adjustment indicates substantial increase in welfare.

In both cases, bulk of surplus goes to consumers, deadweight loss is small.
Why is Welfare rising?

Conduct counterfactuals under alternative evolutions of the auto industry.

1. Market Structure.
2. Observable product offerings.
3. Product quality and marginal cost improvements.

See which have largest impact on consumer surplus gains...
Consumer Surplus varying Market Structure
Consumer Surplus varying Product Set - Observables
Consumer Surplus varying Quality and Cost Trends
Conclusion

We (as a field) have the tools to analyze long term trend in industry evolution.

In US automobiles: welfare increases due to more/better products (big) and decreased ownership concentration (small).

(Old) Lesson: Measuring welfare is more conceptually attractive than markups if products are changing.

(Familiar) Caveat: We are focusing on price competition, dynamic competitive effects need to be considered.
Substitution to the Outside Good

Ideally, we would measure substitution to the outside good with second choice moment, but this is not available.

We do allow strength of outside good to vary with income, based on purchase probabilities by income.

Our Strategy
Vary market size definition.
- Option 1: Number of Households
- Option 2: Number of Households scaled by average duration of a new car ownership.
- Include time fixed effects so outside option is year-specific.
### Model Predicted Substitution

<table>
<thead>
<tr>
<th>First Choice</th>
<th>First most popular second choice</th>
<th>Second most popular second choice</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Trucks</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ford f series</td>
<td>chevrolet silverado 33.6%</td>
<td>ram pickup 24.3%</td>
</tr>
<tr>
<td>nissan frontier</td>
<td>ford f series 20.3%</td>
<td>toyota tacoma 19.3%</td>
</tr>
<tr>
<td><strong>SUVs</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>nissan rogue</td>
<td>honda cr-v 7.5%</td>
<td>toyota rav4 6.9%</td>
</tr>
<tr>
<td>ford explorer</td>
<td>ford escape 6.5%</td>
<td>chevrolet equinox 5.9%</td>
</tr>
<tr>
<td>fiat 500x</td>
<td>volkswagen tiguan 5.5%</td>
<td>ford escape 5.4%</td>
</tr>
<tr>
<td>porsche macan</td>
<td>bmw x5 4.8%</td>
<td>audi q5 3.8%</td>
</tr>
<tr>
<td><strong>Vans</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>nissan quest</td>
<td>toyota sienna 17.4%</td>
<td>honda odyssey 16.1%</td>
</tr>
<tr>
<td>dodge caravan</td>
<td>chrys. town-country 13.1%</td>
<td>honda odyssey 7.4%</td>
</tr>
<tr>
<td><strong>Cars</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ford mustang</td>
<td>chevrolet camaro 8.9%</td>
<td>dodge challenger 7.4%</td>
</tr>
<tr>
<td>dodge viper</td>
<td>chevrolet corvette 15.0%</td>
<td>tesla model s 9.6%</td>
</tr>
<tr>
<td>honda accord</td>
<td>toyota camry 7.3%</td>
<td>toyota corolla 5.9%</td>
</tr>
<tr>
<td>bmw 3 series</td>
<td>mercedes c-class 9.2%</td>
<td>audi a3 3.7%</td>
</tr>
<tr>
<td>lexus es350</td>
<td>acura tlx 6.0%</td>
<td>lexus is250/350 5.4%</td>
</tr>
<tr>
<td>vw passat</td>
<td>volkswagen jetta 10.4%</td>
<td>ford fusion 3.8%</td>
</tr>
</tbody>
</table>

Note: The percent of those consumers switching to an inside good that choose that particular product. For 2015.

1 Older Version of Estimates