# ECON 600: Industrial Organization

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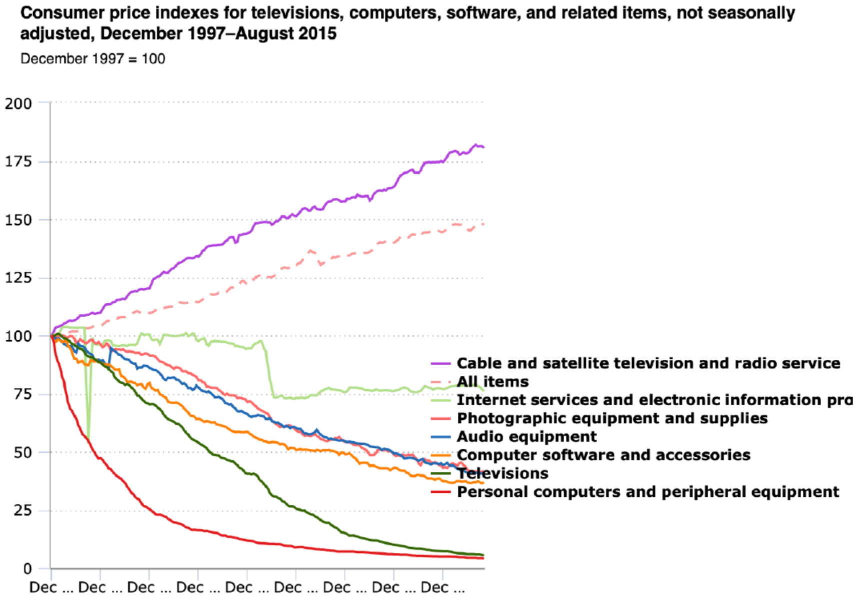
# Dynamic Demand: Durable Goods

# Durable Goods

- Cases in which dynamics matter for durable good purchases:
- Transaction costs and resale markets.
  - E.g. scrappage policy.
- Evolving technology/quality.
  - Buy today v.s. wait for tomorrow?
  - Price elasticity depends on consumers beliefs aboout evolution of quality/price.
  - Firm's optimal pricing problem should take account of dynamics $\rightarrow$ lowering price today can cannibalize own sales tomorrow.

# High Tech Durables CPI



# High Tech Durables CPI

- Today, a 55" 4K LCD TV costs $250. In 2006, a 32" 720P TV cost >$10,000.
  - From August 2–5 to August 2015, prices declined by 87.2%.
- Quality also changes: Reduction in the price of "a TV" understates effect of technological change.
  - BLS try to do chaining or quality adjustments in CPI.
- Static demand estimation seems inappropriate in this environment.
  - If consumers have rational expectations about evolution of *price* and *quality*.
  - Think about decision to buy electric car.

# Gowrisankaran and Rysman (2012): Camcorders

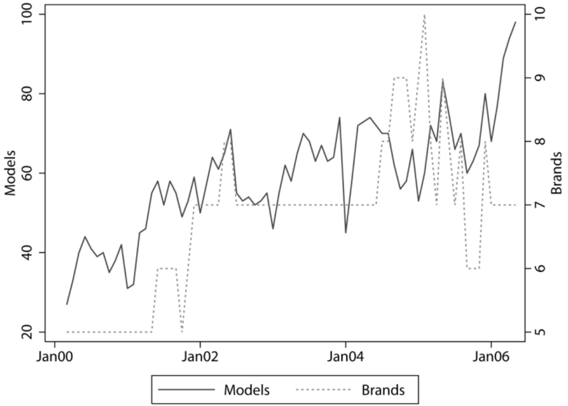
Figure 1: Average non-indicator characteristics over time

# Gowrisankaran and Rysman (2012): Camcorders

- Dynamic model of camcorder purchases during a period of.
  - Falling prices.
  - Increasing quality.
- Allows for:
  - Forward looking consumers to delay adoption.
  - Preferences heterogeneity: early adopters are (endogenously) different from late adopters.
  - Price endogeneity: time-varying unobservable quality $\xi_{jt}$ potentially correlated with price.

# Gowrisankaran and Rysman (2012): Data

- Model-month level *market share* data (market is a month, $t$).
  - Like BLP.
  - Contrast to Hendel and Nevo, Rust etc.
- Sales, price, other characteristics from 383 model from 2000-2006.



# Gowrisankaran and Rysman (2012): Model

- Flow utility to consumer $i$ from buying model $j$ at time $t$:

$$u_{ijt} = x_{jt}\alpha_i^x - \alpha_i^p \ln(p_{jt}) + \xi_{jt} + \epsilon_{ijt}$$

- $x_{jt}$ includes camcorder attributes (size, zoom, screen size).
- $p_{jt}$ is price.
- $\xi_{jt}$ is time-varying unobserved quality.

# Gowrisankaran and Rysman (2012): Model

- Flow utility to consumer $i$ from holding model $j$ at time $t$ (previously purchased):

$$u_{ijt} = x_{jt}\alpha_i^x + \xi_{jt} + \epsilon_{ijt}$$

- Flow utility to consumer $i$ from holding nothing:

$$u_{i0t} = \epsilon_{i0t}$$

- Consumers can upgrade at zero cost
  - No second hand market.
- Once consumers own a model, $j$ they can never go back to owning model 0 "nothing".
- For notational convenience, let's denote $u_0$ as the flow utility of whatever the consumer currently owns.

# Gowrisankaran and Rysman (2012): Model

$$u_{ijt} = x_{jt}\alpha_i^x - \alpha_i^p \ln(p_{jt}) + \xi_{jt}$$
$$(\alpha_i^x, \alpha_i^p) \sim N\left((\alpha^x, \alpha^x), \Sigma\right)$$

- $\Sigma$ diagonal.
- Note that this is the population distribution of preferences.
  - Not the distribution of preferences conditional on holding model $j$ at date $t$.

# Gowrisankaran and Rysman (2012): Model

- Consumer's dynamic problem (dropping $i$):

$$V(u_0, \Omega) = E_\epsilon[\max\{u_0 + \beta E[V(u_0, \Omega')|\Omega] + \epsilon_0, \\ \max_{j \in 1 \dots J}\{u_j + \beta E[V(u_j, \Omega')|\Omega] + \epsilon_j\}]$$

- $\Omega$ is the market state that includes all prices and product characteristics (including $\xi_{jt}$), as well as current endowments.
  - Everything that determines product characteristics and evolution of product characteristics.
- Suppose $\Omega$ evolves according to a Markov process.
  - Consistent with a supply model where products enter exogenously, and price is set each period in a Markov perfect equilibrium.

# Gowrisankaran and Rysman (2012): Model

$$V(u_0,\Omega) = E_\epsilon[\max\{u_0 + \beta E[V(u_0,\Omega')|\Omega] + \epsilon_0, \max_{j\in 1\ldots J}\{u_j + \beta E[V(u_j,\Omega')|\Omega] + \epsilon_j\}]$$

- Rewrite using Logit:

$$V(u_0,\Omega) = \log\left[exp\left(u_0 + \beta E[V(u_0,\Omega')|\Omega]\right) + \sum_{j\in 1\ldots J} exp\left(u_j + \beta E[V(u_j,\Omega')|\Omega]\right)\right]$$

- Rewrite using inclusive value:

$$V(u_0,\Omega) = \log\left[exp\left(u_0 + \beta E[V(u_0,\Omega')|\Omega]\right) + exp(\delta(\Omega))\right]$$

$$\delta(\Omega) = log\left[\sum_{j\in 1\ldots J} exp\left(u_j + \beta E[V(u_j,\Omega')|\Omega]\right)\right]$$

# Gowrisankaran and Rysman (2012): Model

$$V(u_0, \Omega) = \log \left[ exp \left( u_0 + \beta E[V(u_0, \Omega')|\Omega] \right) + exp(\delta(\Omega)) \right]$$

$$\delta(\Omega) = log \left[ \sum_{j \in 1 \ldots J} exp \left( u_j + \beta E[V(u_j, \Omega')|\Omega] \right) \right]$$

- $\delta(\Omega)$ is the PDV of upgrading to the preferred option at state $\Omega$.
- Notice that $\Omega$ affects $V(u_0, \Omega)$ <u>only through</u> current $\delta(\Omega)$ and predictions of future $\delta(\Omega)$

# Inclusive Value Sufficiency (Again)

$$V(u_0, \Omega) = \log \left[ exp\left(u_0 + \beta E[V(u_0, \Omega')|\Omega]\right) + exp(\delta(\Omega))\right]$$

$$\delta(\Omega) = log \left[ \sum_{j \in 1 \ldots J} exp\left(u_j + \beta E[V(u_j, \Omega')|\Omega]\right) \right]$$

- Assume: $g(\delta(\Omega')|\Omega) = g(\delta(\Omega')|\tilde{\Omega})$ if $\delta(\Omega) = \delta(\tilde{\Omega})$.
- $\delta(\Omega)$ is a sufficient statistic for predictions about future $\delta(\Omega)'$.
  - Substantive assumption.

# Inclusive Value Sufficiency (Again)

- To compute the continuation values for each choice $E[V(f_j, \Omega')|\Omega]$, only need to condition on $\delta$:

$$V(u_0, \delta) = \log\left[exp\left(u_0 + \beta E[V(u_0, \delta')|\delta]\right) + exp(\delta)\right]$$

$$\delta = log\left[\sum_{j \in 1 \ldots J} exp\left(u_j + \beta E[V(u_j, \delta')|\delta]\right)\right]$$

- Reduces state space to a single index for each consumer.
  - Note that $\delta_{it}$ is consumer type specific because it depends on $(\alpha_i^x, \alpha_i^p)$ which enter $u_j$.
  - Also $V_i$ is consumer type specific...

# Inclusive Value Sufficiency (Again)

- Specify functional form for evolution of $\delta$:

$$\delta_{t+1} = \gamma_1 + \gamma_2 \delta_t + v_{t+1}$$

$$v_t \sim N(0, \sigma_v)$$

- Notice that if $\gamma_2 \in (0, 1)$, consumers expect $\delta$ to converge to $\gamma_1/(1-\gamma_2)$.
  - Intuitively, $\delta < \gamma_1/(1-\gamma_2)$ early in the data,and inclusive value expected to rise because of falling prices and improved products.

# Gowrisankaran and Rysman (2012): Model

- Solving the model for the optimal policy (purchase decisions) requires:

$$V(u_0, \delta) = \log \left[ exp \left( u_0 + \beta E[V(u_0, \delta')|\delta] \right) + exp(\delta) \right]$$

$$\delta = log \left[ \sum_{j \in 1 \ldots J} exp \left( u_j + \beta E[V(u_j, \delta')|\delta] \right) \right]$$

$$\delta_{t+1} = \gamma_1 + \gamma_2 \delta_t + v_{t+1}$$

- All three equations to hold.

# Gowrisankaran and Rysman (2012): Estimation

- If we had micro-data (as in Hendel and Nevo) we'd be done.
  - Solve model and compute likelihood.
- But here, we have market shares.
  - And a product-market unobservable $\xi_{jt}$ (rationalizes market shares).
- Idea: for each $\theta$, need to iterate between solving dynamic model and performing the BLP contraction mapping...

# Estimation: Step One (Inner Loop)

1. Guess parameters, $\theta = (\alpha, \Sigma_\alpha)$.
2. Initialize values functions $V(u_0, \delta) = 0$.
3. Initialize $\xi = 0$
4. Given value functions, can compute inclusive values:
$$\delta = log\left[\sum_{j\in 1\ldots J} exp\left(u_j + \beta E[V(u_j,\delta')|\delta]\right)\right]$$
5. Draw consumers from $F(\alpha_i)$ (e.g. grid of types). Estimate $\delta_{it+1} = \gamma_1 + \gamma_2\delta_{it} + v_{t+1}$
6. Iterate Bellman equation:
$$V(u_0,\delta) = \log\left[exp\left(u_0 + \beta E[V(u_0,\delta')|\delta]\right) + exp(\delta)\right]$$
$$\delta = log\left[\sum_{j\in 1\ldots J} exp\left(u_j + \beta E[V(u_j,\delta')|\delta]\right)\right]$$
7. Repeat from (4) until convergence

# Estimation: Step Two (Middle Loop)

1. You have solved for $V_i(u_0, \delta)$ for a fixed vector of parameters $\theta$ and unobservables $\xi$.

2. Simulate market shares.

   2.1 Draw consumers at date 0 from $F(\alpha_i)$.
   2.2 Simulate purchases for each consumer, move to date 1.
   2.3 etc. Keeping track of what model each consumer holds.

3. This generates model-implied market shares for eahch period: $\hat{s}_{jt}(\theta, \xi)$.

4. Perform BLP contraction mapping by comparing $\hat{s}_{jt}(\theta, \xi)$ to observed $s_{jt}$.:

$$\xi' = \xi + log(s_{jt}) - log(\hat{s}_{jt}(\theta, \xi))$$

5. Notice that on each iteration, you have to go back and do step one (the inner loop) over again!

# Estimation: Step Three (Outer Loop)

1. Now you can take a parameters vector, $\theta$, and compute the unobservables, $\xi$, that rationalize the observed market shares!
2. The rest of the estimation is just like BLP.
3. Form moments, $E(\xi_{jt} z_{jt}) = 0$
4. Apply GMM.

- BLP + dynamic consistency restriction.
- Have to assume a unique fixed point exists for this whole thing (try different starting values).

# Identification & Instruments

- Identification is similar to BLP.
- The addition of dynamic consistency in choices actually provides additional identifying power.
  - Intertemporal substitution.
  - E.g. a price reduction for a low quality mode at date $t$ should induce substitution from similat models at date $t+1$.
- BLP-type instruments:
  - Model characteristics of same and other firms.
  - Model count of same and other firms.
- Note: cannot directly observe repeated purchases (or who bought what).
  - Micro-data would add identifying power.

# G&R: Results

TABLE 1
PARAMETER ESTIMATES

| Parameter | Base Dynamic Model (1) | Dynamic Model without Repurchases (2) | Static Model (3) | Dynamic Model with Micro Moment (4) |
|---|---|---|---|---|
| Mean coefficients ($\alpha$): | | | | |
| Constant | −.092 (.029)* | −.093 (7.24) | −6.86 (358) | −.367 (.065)* |
| Log price | −3.30 (1.03)* | −.543 (3.09) | −.099 (148) | −3.43 (.225)* |
| Log size | −.007 (.001)* | −.002 (.116) | −.159 (.051)* | −.021 (.003)* |
| (Log pixel)/10 | .010 (.003)* | −.002 (.441) | −.329 (.053)* | .027 (.003)* |
| Log zoom | .005 (.002)* | .006 (.104) | .608 (.075)* | .018 (.004)* |
| Log LCD size | .003 (.002)* | .000 (.141) | −.073 (.093) | .004 (.005) |
| Media: | | | | |
| DVD | .033 (.006)* | .004 (1.16) | .074 (.332) | .060 (.019)* |
| Tape | .012 (.005)* | −.005 (.683) | −.667 (.318)* | .015 (.018) |
| Hard drive | .036 (.009)* | −.002 (1.55) | −.647 (.420) | .057 (.022)* |
| Lamp | .005 (.002)* | −.001 (.229) | −.219 (.061)* | .002 (.003) |
| Night shot | .003 (.001)* | .004 (.074) | .430 (.060)* | .015 (.004)* |
| Photo capable | −.007 (.002)* | −.002 (.143) | −.171 (.173) | −.010 (.006) |
| Standard deviation coefficients ($\Sigma^{1/2}$): | | | | |
| Constant | .079 (.021)* | .038 (1.06) | .001 (1,147) | .087 (.038)* |
| Log price | .345 (.115)* | .001 (1.94) | −.001 (427) | .820 (.084)* |

NOTE.—Standard errors are in parentheses. All models include brand dummies, with Sony excluded. There are 4,436 observations.

* Statistically significant at the 5 percent level.

- Column 4 includes micro-moment on penetration (share of households holding some model).

# G&R: Results

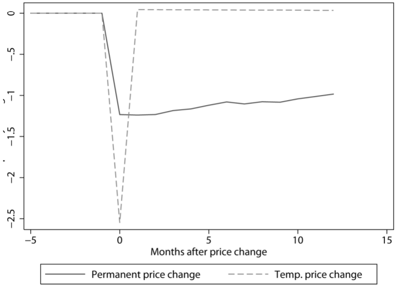



FIG. 12.—Industry dynamic price elasticities

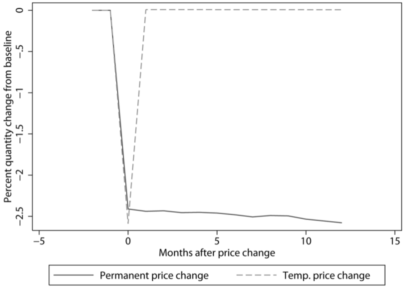
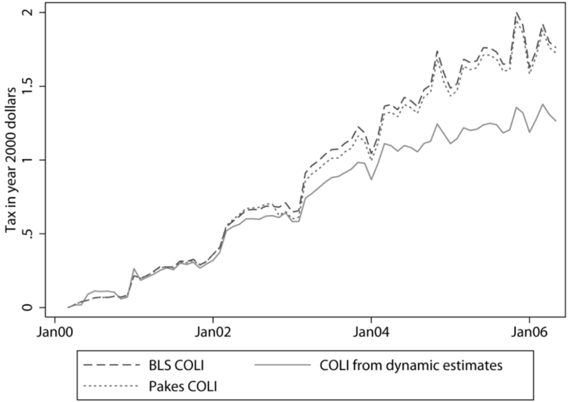



FIG. 13.—Dynamic price elasticities for Sony DCRTRV250

# G&R: Results




- BLS and Pakes COLI are basically Laspeyres: $\frac{\sum_j p_{jt+1} s_{jt}}{\sum_j p_{jt} s_{jt}}$ - shows how the value of the market increasing over time.
- COLI from model is essentially growth in mean utility from sales at date $t$. Notice divergence.
  - Dynamic selection of heterogeneous consumers.

# Hodgson (2023)

- Durable goods demand with a *resale market*.
  - Also see Schrialdi (2011).
- Combine BLP approach with micro-moments.
  - Can see which consumers upgraded from $j$ to $k$ at each date.

# Hodgson (2023): Setting

- Market for Business Jets: 1961-2000.
- Concentrated market for new jets.
- Active resale market.
- Data on full history of ownership from FAA.

Table 1: Market Share by Manufacturer

| | New Market Share 1961 - 2000 | | | Used Market | |
|---|---|---|---|---|---|
| Manufacturer | Small | Medium | Large | Resale Ratio | Annual Used Sales |
| Bombardier | 32% | 8% | 33% | 23.3% | 309.6 |
| Cessna | 52% | 11% | 0% | 26.6% | 392.2 |
| Dassault | 4% | 22% | 14% | 26.6% | 165.8 |
| Gulfstream | 0% | 0% | 54% | 19.7% | 88.8 |
| IAI | 0% | 14% | 0% | 29.5% | 100.0 |
| Raytheon | 10% | 26% | 0% | 25.2% | 168.6 |

# Hodgson (2023): Setting

- Why do manufacturers accept own brand trade-ins?
  - If there are transaction costs to upgrading, consumers will hold old models when they might prefer to buy a new model.
  - Trade-ins modeled as a way to reduce transaction costs for <u>upgrading consumers</u>.
- But trade-ins are resold on the used market!
  - Increase in supply of used jets can cannibalize new jet sales.
  - <u>First time buyers</u> benefit from lower used jet prices.

# Hodgson (2023): Model

- Consumer $i$ gets flow utilities:

$$\begin{aligned} u^i_{jjt} &= \gamma_{ijt} + \epsilon_{ijt} \\ u^i_{kjt} &= \gamma_{ijt} + \tilde{\gamma}_{kj} + (p_{kt} - p_{jt})\, \alpha^p_i - \tau_{ikj} + \epsilon_{ijt} \\ u^i_{k0t} &= p_{kt}\alpha^p_i - \tau_{ik0} + \epsilon_{i0t}. \end{aligned}$$

- $\tau_{ijk}$ is the transaction cost for upgrading from $j$ to $k$.
- Unlike in G&R, consumers can sell model $j$ and drop out of market (alternative 0).
- Assume $\tau_{ijk}$ is reduced if $j$ and $k$ same brand and $k$ is new (same-brand trade in):

$$\tau_{ikj} = \left(\tau - new_{jt} 1(m(j) = m(k)) b_{m(j)}\right) 1(j \neq 0) + \tau^{exit} 1(j = 0) + \nu^{\tau}_i$$

# Hodgson (2023): Model

$$V_i(k, \Omega_{it}, \epsilon_{it}) = \max_{k \in J_t \cup 0} \left\{ u^i_{j(i,t)k} + \epsilon_{ikt} + E\left[\delta_{ikt+1} | \Omega_{it}\right] \right\}$$

- Consumer's problem looks pretty similar to G&R.
- Make inclusive value assumption.
- Now, inclusive value depends on what model you currently hold.
    - eligibility for trade-ins varies by model held.

# Hodgson (2023): Estimation

- Estimation uses BLP-moments and micro-moments:

Table 5: Micro-Moments

| | Moment | | Related Parameters |
|---|---|---|---|
| 1 | Upgrade conditional on holding | $P\left(upgrade_{it} \mid j_{it} \neq 0\right)$ | $\tau$ |
| 2 | Exit conditional on holding | $P\left(j_{it+1} = 0 \mid j_{it} \neq 0\right)$ | $\tau^{exit}$ |
| 3 | New jet conditional on upgrade | $P\left(age(j_{it+1}) \leq 1 \mid upgrade_{it} = 1\right)$ | $\alpha^{new}_{upgrade}$ |
| 4 | New jet conditional on first purchase | $P\left(age(j_{it+1}) \leq 1 \mid first_{it} = 1\right)$ | $\alpha^{new}$ |
| 5 | Same brand conditional on upgrade | $P\left(m(j_{it+1}) = m(j_t) \mid upgrade_{it} = 1\right)$ | $\alpha^{sb}$ |
| 6-12 | Difference in new jet share between same-brand upgrades and brand switchers | $P\left(age(j_{it+1}) \leq 1 \mid m = m(j_{it+1}) = m(j_t)\ \&\ upgrade_{it} = 1\right)$ $-P\left(age(j_{it+1}) \leq 1 \mid m = m(j_{it+1}) \neq m(j_t)\ \&\ upgrade_{it} = 1\right)$ | $b_m, \sigma_m$ |
| 13-15 | Expected purchase price conditional on upgrading from jets of different ages | $E(price(j_{it+1}) \mid age(j_{it} < 5)\ \&\ upgrade_{it} = 1)$ $E(price(j_{it+1}) \mid age(5 \leq j_{it} < 15)\ \&\ upgrade_{it} = 1)$ $E(price(j_{it+1}) \mid age(15 \leq j_{it})\ \&\ upgrade_{it} = 1)$ | $\sigma_p, \sigma_{p\tau}$ |
| 16-18 | Exit conditional on holding jets of different ages | $P\left(j_{it+1} = 0 \mid age(j_{it} < 5)\right)$ $P\left(j_{it+1} = 0 \mid age(5 \leq j_{it} < 15)\right)$ $P\left(j_{it+1} = 0 \mid age(15 \leq j_{it})\right)$ | $\sigma_0$ |
| 19 | Upgrade conditional on past upgrade | $P\left(upgrade_{it} \mid j_{it} \neq 0\ \&\ \max_{\tilde{t}<t}\{upgrade_{i\tilde{t}}\} = 1\right)$ | $\sigma_\tau$ |
| 20 | Brand held before conditional on upgrade | $P\left(m(j_{it+1}) \in \{m(j_{i\tilde{t}})\}_{\tilde{t}<t} \mid upgrade_{it} = 1\right)$ | $\sigma_m$ |

# Hodgson (2023): Results

Table 7: Demand Simulations

| | Baseline Parameters | | |
|---|---|---|---|
| | No Buyback | Buyback | Δ |
| (1) Upgrades to New | 1193.0 | 1635.4 | 442.4 |
| (2) Upgrades to Used | 3185.1 | 3056.4 | -128.7 |
| (3) Exits | 16700.0 | 16689.0 | -11.0 |
| Used Jet Supply to First Time Buyers = (1) + (3) | 17893.0 | 18324.4 | 431.4 |

Table 8: Equilibrium Simulations

| | Baseline Parameters | | |
|---|---|---|---|
| | No Buyback | Buyback | Δ |
| Upgrades to New | 1304.8 | 1635.4 | 330.6 |
| Used Jet Supply to First Time Buyers | 17834.8 | 18324.4 | 489.6 |
| New Sales to First time Buyers | 6131.6 | 6004.9 | -126.7 |
| Average Used Jet Price ($ Million) | 5.85 | 5.64 | -0.21 |
| Manufacturer Profit ($ Billion) | 8.0 | 9.4 | 1.4 |
| Consumer Surplus ($ Billion) | 215.2 | 220.3 | 5.1 |

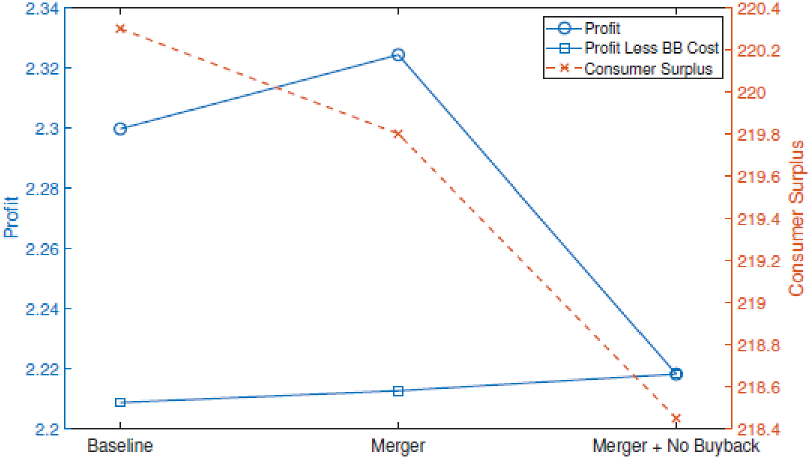
- Solve for equilibrium new and used jet prices.
  - Firms maximize static profit.
  - All used jet markets clear!

# Hodgson (2023): Results

- Use the estimated model that under reasonable assumptions on the cost of trade-ins to the firm...
  - e.g. firms eat the transaction costs that consumers don't have to pay if they trade in.
- Then all firms offering trade-ins is a prisoners' dilemma equilibrium!
  - Cessna only accepts trade-ins because all other firms accept trade-ins.
- Under a hypothetical merger between Cessa and Learjet, trade-ins would no longer be optimal.

# Hodgson (2023): Results

Figure 3: Simiulated Effects of Merger



# Hodgson (2023)

- By the way, this started out as my second year paper.
  - No dynamics in first version.
  - Repeated static choice.
- Started work 2015 - published 2023.
- Try to be faster than this.

# Next Time

- Estimation of dynamic discrete choice games
- Bajari, Benkard, and Levin (2007)