Computing Price-Cost Margins in a Durable Goods Environment

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Preliminary

Introduction.

- We typically cannot observe marginal cost.
- Methods for computing marginal cost from demand and equilibrium assumptions are popular.
- How should we proceed in a dynamic environment?
- In particular, digital camcorders, which are durable.

Why estimate marginal costs for durable goods?

- To understand market power in the industry.
  - Can use cost estimates to compute price-cost margins.
- To evaluate when innovation is occurring in this sector.
  - Useful to understand if competition or concentration is causing cost reductions.
- To understand the extent to which forward-looking firm behavior matters.
  - For instance, smaller firms may mostly cannibalize other firm sales.
- Run counterfactual experiments, e.g. merger simulations.
  - Long-term goal: Why do prices fall in this industry?

Static approach.

- Estimate demand.
- Impose equilibrium assumption.
- Compute marginal revenue.
  - If price-setting, we need to invert to get MR wrt Q.
- Theory says this is marginal cost.

With dynamics:

- Derivative of marginal revenue is dynamic.
- It incorporates the change in current market share AND the change in the future stream of profits.

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- Derivative of marginal revenue is dynamic.
- It incorporates the change in current market share AND the change in the future stream of profits.
- In a durable goods framework:
  - a lower price today steals consumers from the future AND
  - affects future pricing decision.

Our model.

Compute marginal revenue in a way that resolves the effect of pricing today on:

- Today's market share.
- Future consumer demand.
- Dynamic strategic interactions.

Problems with dynamics.

1. Computational: Large state space.
2. Theoretical: Multiple equilibria.

- We borrow from Berry & Pakes (2000) and Bajari, Benkard & Levin (2005) address these issues.
- However, BP and BBL rely on do not derive the value of marginal cost that rationalizes each price.
  - Loosely, they identify the parameters in the marginal cost function, but not the error term.
  - If the error term is a large component of marginal cost, our analysis of marginal cost will be erroneous.

More literature

- Finding MC for each price associated with Bresnahan (1987) and Berry, Levinsohn & Pakes (1995).
- Auction equivalent: Gurre, Perrigne & Vuong.
- Closest may be Pesendorfer & Jofre-Bonet (2003) in an auction framework (with different goals).
- Other papers that find MC in a dynamic framework:
  - Estaban & Shum (2007), Goettler & Gordon (2011), Kim (2014).

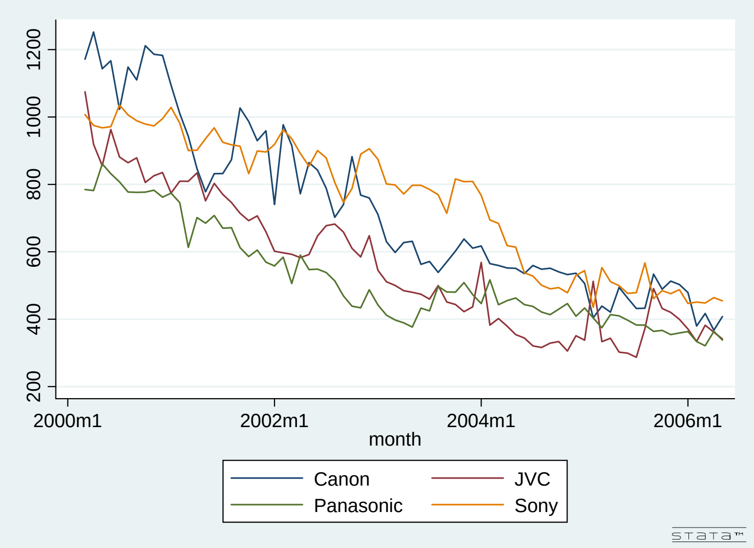
Our approach.

Step 1 Estimate reduced-form approximation of pricing strategy. (BBL)

Step 2 Construct dynamic FOC and invert to compute MC. (BLP)

- Assume there is a final period, and proceed by backwards induction.
- In each period, compute current market share and expected future profits.
    - Use Step 1 to predict prices in the future.
    - But we use structural transitions from our demand model.
- Change one price by 5%, and recompute.
- Compute MR from price change.
- Invert to obtain marginal cost.

Price by time, “Big 4" firms.



Results:

- Marginal costs for firms are lower when we include dynamics!
- Even lower for firms with large market shares.
  - Dynamics significant in preventing Sony (60%+) from lowering prices early on.
- Price-cost margins fall over time.
- High value products have higher price-cost margins.
- More work to do ...

Basic consumer model.

- Mass of consumers M.
- Discrete time, live forever.
- Consumers make a discrete choice what to buy or to wait each period.
- Product is infinitely durable.
- Consumers hold one good at a time.
- Consumer holdings described by H_t.

Demand.

- Share to j in t is $s_{jt}(P_t, H_t)$.
    - P_t is vector of prices.
- Consumer holdings evolve:

$$H_{t+1} = g_1(H_t, S_t, P_t, \Omega_t^c)$$

    - Ω_t^c are state variables for consumer.

Model of firms.

- Firms are indexed by $f = 1, \ldots, F$.
- Each period, there are J_t products available.
- Firm f produces all $j \in \mathfrak{F}_{ft}$.
- Each product has a mean flow utility and a marginal cost mc_{jt}.
- Product utilities (past, present and future) are known and exogenous.
- Firms know all current marginal costs but have uncertainty over all future marginal costs.
    - Information is symmetric across firms.
- Firm picks price p_{jt} for all $j \in \mathfrak{F}_{ft}$.

Profits.

- State space for firms: $\widehat{\Omega}_t$.
- Transitions are Markov: $\widehat{\Omega}_{t+1} = g_2(P_t, \widehat{\Omega}_t)$.
- Value function:

$$V(\widehat{\Omega}_{ft}) = \max_{P_{ft}} E\left[\sum_{\tau=t}^{\infty} \sum_{j \in \mathfrak{F}_{f\tau}} \left(p_{j\tau} - mc_{j\tau}\right) Ms_{j\tau}(S_\tau, P_\tau) \middle| \widehat{\Omega}_{ft}\right].$$

First-order condition.

- Markov Perfect Equilibrium.
- First-order condition for price jt:

$$s_{jt}(S_t, P_t) + \sum_{k \in \mathfrak{F}_{ft}} (p_{kt} - mc_{kt}) \frac{\partial s_{kt}(S_t, P_t)}{\partial p_{jt}} + \beta \frac{\partial}{\partial p_{jt}} E\left[V_f(\widehat{\Omega}_{ft+1}) | \widehat{\Omega}_{ft}, P_t \right] = 0.$$

- Plan: Use this equation to compute marginal cost.

Consumer demand, with detail.

We follow Gowrisankaran & Rysman (2012) exactly.

- The mean flow utility of product *j* in period *t* to consumer *i* is δ^f_{ijt}.
- Flow utility in period of purchase:

$$u_{ijt} = \delta^f_{ijt} - \alpha_i \ln(p_{jt}) + \varepsilon_{ijt}.$$

- ε_{ijt} is iid EV.
- $\delta^f_{ijt} = \overline{\delta}^f_{jt} + \sigma_1 \nu_{i1}$.
- $\alpha_i = \alpha + \sigma_2 \nu_{i2}$.
- ν_{i1}, ν_{i2} distributed $\mathcal{N}(0, 1)$
- α, σ_1 and σ_2 are to be estimated.

Modeling consumer holdings.

- Consumers track flow utility of the product they own: δ_{it}^{0}.
- $\delta_{it}^{0} = 0$ for $t = 1$, up until time of first purchase.
- $\delta_{it}^{0} = \delta_{jt}^{f}$ for t after purchase.

Modeling purchase options.

- The logit inclusive value (δ_{it}) captures the value of purchase.
- The inclusive value:

$$\delta_{it} = \ln \sum_{j \in J_t} \exp\left(\delta^f_{ijt} + \beta E\left[V^c_i(\delta^f_{ijt}, \delta_{it+1}) \middle| \delta_{it} \right]\right)$$

  - V^c_i is the consumer value function.

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Assumption: Inclusive Value Sufficiency (IVS):

$P(\delta_{it+1}|\Omega^c_t) = P(\delta_{it+1}|\delta_{it})$.

- Consumers predicts the future distribution of δ_{it} based only on current δ_{it}, rather than all of Ω^c.
- Reduces the state space!

Expectations

- We implement IVS with an AR1 function form:

$$\delta_{it+1} = \gamma_{0i} + \gamma_{1i}\delta_{it} + \eta_{it}$$

- We estimate these parameters from δ_{it} in our model.
  - Thus, we impose rational expectations.
- The parameters $\{\gamma_{0i}, \gamma_{1i}, \sigma_i^{\nu}\}$ represent future expectations.

Consumer value function.

- IVS provides two important simplifications:
  1. Value function depends on two scalars (δ_{it}^0 and δ_{it}).
  2. Reduced-form approximation of the supply side means we can estimate demand separately from supply.
- Consumer value function:

$$V_i^c(\delta_i^0, \delta_i) = \ln\left(\exp(\delta_i) + \exp\left(\delta_i^0 + \beta E\left[\, V_i^c(\delta_i^0, \delta_i') \middle|\, \delta_i \right]\right)\right).$$

- For a given vector of mean utilities, we solve for Bellman, AR1, and IV simultaneously.

Solving for mean utilities.

- Consumer solution implies market shares for each type i and period t.
- We aggregate over types to get a predicted market share $\widehat{s}_{jt}$.
- We use a BLP fixed point equation to solve for mean utilities:

$$\overline{\delta}_{jt}^{f} = \overline{\delta}_{jt}^{f} + \ln(s_{jt}^{*}) - \ln(\widehat{s}_{jt}^{*})$$

Consumer problem.

Solve simultaneously for:

δ_{it}	Logit inclusive value.
$\{\gamma_{0i}, \gamma_{1i}, \sigma_i^{\eta}\}$	AR1 approximation of expectations.
V_i^c	Value function from Bellman.
$\overline{\delta}_{jt}^f$	Mean flow utilities.

- Use simulation over *i*.
  - For elements indexed by *i*, we must solve separately for each draw *i*.

Consumer problem overview.

- Demand is a random-coefficient logit model with RCs on the constant term and price only.
- Consumers hold 1 good at a time.
- Product is infinitely durable.
- Consumers can update their product today or wait.
- Consumers have rational expectations about the future evolution of offerings, based on a reduced-form approximation of how the supply side evolves.

Implication:

More sales today imply lower sales the next period.

Computing marginal cost: Step 1

- Let Ω_t equal $\widehat{\Omega}_t$ but for the marginal costs.
  - Ω_t consists of the state variables that are observable to the econometrician.
- Let $P_t = \psi(\Omega_t, U_t)$.
  - U_t is the vector of random draws for all products in t.
  - Distribution of U_t is related to distribution of MC_t.
- Step 1: Specify functional form for ψ and estimate.

Computing marginal cost: Step 2

- There is a final period T, past what we observe in the data.
  - In practice, we assume product offerings stay the same as the last period in the data.
- Draw ns values of U_t^s, $s = 1, \ldots, ns$.
  - Distribution is based on results of first-step estimation.
- Compute the distribution of prices for each product and period.

$$P_t^s = \psi(\Omega_t, U_t^s).$$

Last period

- FOC in last period:

$$s_{jT}(P_T^s, H_T) + \sum_{k \in \mathfrak{F}_{fT}} (p_{kT}^s - mc_{kT}^s) \frac{\partial s_{kT}(P_T^s, H_T)}{\partial p_{jT}^s} = 0.$$

- Matrix notation:

$$P_{fT}^s + \Lambda_{fT}^{s,-1} S_{fT}(P_{fT}^s, H_t) = MC_{fT}^s.$$

- Λ_{ft} is the matrix $\partial S_{ft} / \partial P_{ft}$.
  - Note: Λ_{ft} is for one firm. All elements are non-zero.
- We obtain a distribution of marginal costs in the last period.

Constructing Λ_{ft}.

- For a given P_T^s, compute $S_{fT}(P_T^s, H_t)$.
- Change one price by a small discrete amount (5%).
  - Call new vector $P_T^{s\prime}$.
- Compute $S_{fT}(P_T^{s\prime}, H_t)$.
- Use discrete approximation to derivative to construct Λ_{ft}.
- That is, element $[k, j]$ is:

$$\Lambda_{ft}[k, j] = \frac{\Delta s_{kT}}{\Delta p_{jT}^s}.$$

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- Use GR to compute market shares even in T.
  - dynamic demand.

Other periods

- FOC in matrix notation:

$$P^s_{fT-1} + \Lambda^{s,-1}_{fT-1}\left(S_{fT-1}(P^s_{fT-1}, H_{T-1}) + \beta \frac{\partial}{\partial P^s_{fT-1}} EV\right) = MC^s_{fT-1}.$$

- $EV = E\left[V_f(\Omega_{fT})|\Omega^s_{fT-1}, P^s_{T-1}\right] =$

$$E\left[V_f(\Omega_{ft})|\Omega^s_{ft-1}, P^s_{t-1}\right] = \frac{1}{ns}\sum_{\tau=t}^{T}\sum_{m=1}^{ns}\sum_{k\in\mathfrak{F}_{f\tau}}(p^{ms}_{k\tau} - mc^{m}_{k\tau})\, s_{k\tau}(P^{ms}_{\tau}, H^s_{\tau}).$$

Computing

- How to compute:

$$E\left[V_f(\Omega_{ft})|\Omega^s_{ft-1}, P^s_{t-1}\right] = \frac{1}{ns}\sum_{\tau=t}^{T}\sum_{m=1}^{ns}\sum_{k\in\mathfrak{F}_{f\tau}}\left(p^{ms}_{k\tau} - mc^m_{k\tau}\right) s_{k\tau}(P^{ms}_{\tau}, H$$

- For each shock m, mc^m is already computed because we are using backward induction.
- Starting from any state in t, we observe holdings H_t.
  - Compute p^s_t from reduced-form equation and shocks.
  - Compute market share $s_t(p^s_t, H_t)$.
  - Implies holdings H^s_{t+1}.
  - Compute prices p^{ms}_{t+1}.
  - Compute shares $s_{t+1}(p^{ms}_{t+1}, H^s_{t+1})$, and thus H^{ms}_{t+2}.
  - Compute prices p^{ms}_{t+2} etc.
- Adjust one starting price by 5%, recompute to get derivative.

Observed prices.

- We now have the distribution of MC in each period.
- We can repeat our solution for MC, but this time substitute observed prices for simulated prices.
- Thus, we find the marginal cost that rationalizes all of the observed prices (conditional on the distribution of future MC that we have computed).

Alternative assumptions:

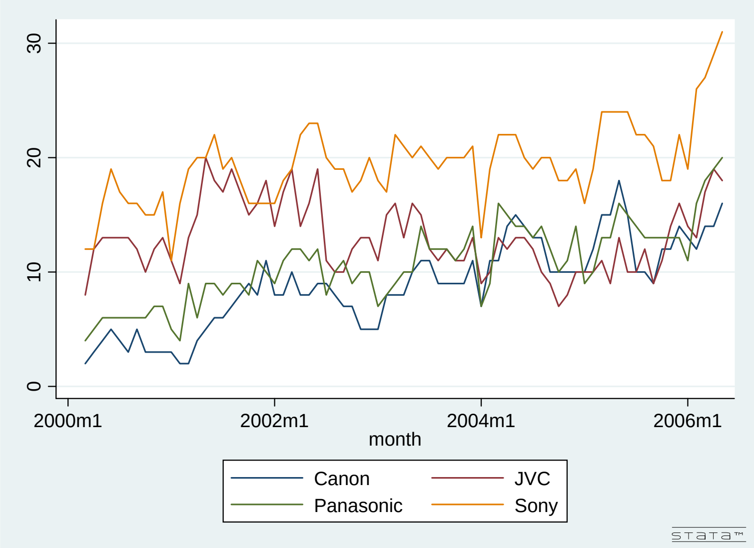
- Perfect foresight of *MC* allows for elegant solution of all *MC* simultaneously.
- We need Λ for all products simultaneously.
- Requires derivative of market share from prices in different periods, and we cannot use simulation to do computation.
- Thus, using simulation changes the solution technique.
- Note, we could also implement asymmetric info in current MC, but that deviates from BLP and is a little harder.

Data.

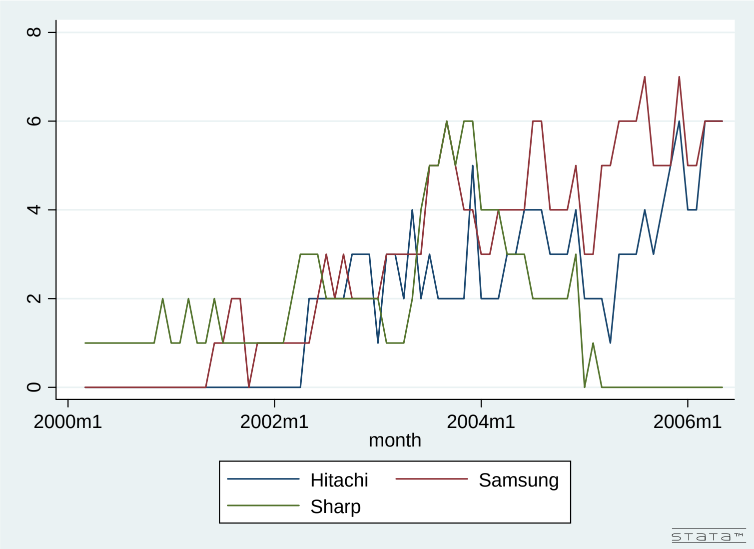
The same as in Gowrisankaran & Rysman (2012).

- Sales and average price for digital camcorders.
- Monthly for March 2000 to May 2006.
- Does not account for Walmart or on-line sales.
- NPD Techworld.
- 383 products, 11 brands, 4,436 observations.

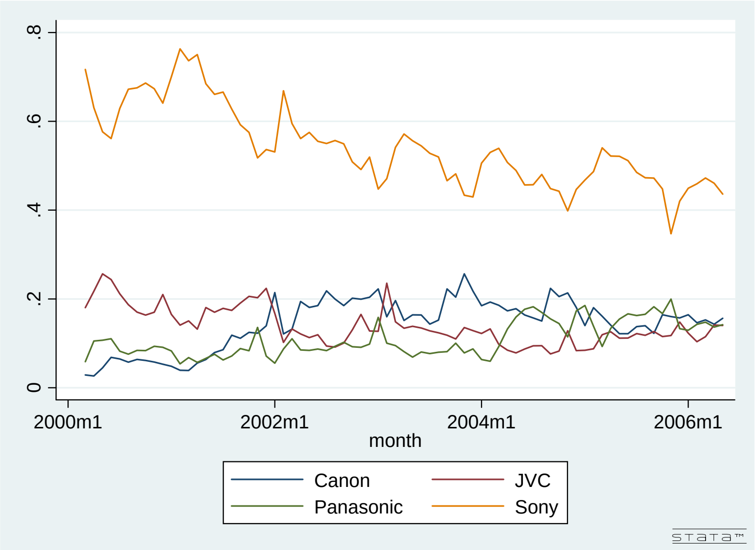
Number of models, “Big 4" firms.



Number of models, “Next 3" firms.



Market share over time, “Big 4" firms.



Summary statistics

Variable	Measurement	Mean	Std.	Min	Max
	Product-level variable				
Product quality	Mean flow utility of product.	0.0008	0.045	-0.12	0.09
	Firm-level variables				
Firm average product quality	Average of mean flow utilities of products owned by the firm excluding product in question.	0.0015	0.022	-0.11	0.06
Firm size	Number of products firm owns	13.75	6.2	1	31
	Market-level variables				
Market average product quality	Average of mean flow utilities of all products in market excluding product in question.	0.0008	0.006	-0.19	0.2
Market size	Number of products in market.	62.56	13.95	27	98
Consumer holdings	Percentage of the population have purchased the good.	0.045	0.03	0	0.1

Implement Step 1.

- Regress price on state variables, but which ones?
- BLP instruments:
  - Product quality.
  - Variables that capture the price-cost margin:
    - Counts of own products and rival products.
    - Average characteristics of own and rival products.
- We use one characteristic: mean utilities $\overline{\delta}_{jt}^{f}$
  - If we had random coefficients on more characteristics, we would use those characteristics also.

Implement Step 1.

Consumer holdings.

- Consumer holdings also predicts prices.
- We use the share of consumers that hold the good.
- Other measures (quality of products they hold, variance across consumer types) had little predictive power.
- Note that in our specification of demand, there is almost no repurchase.

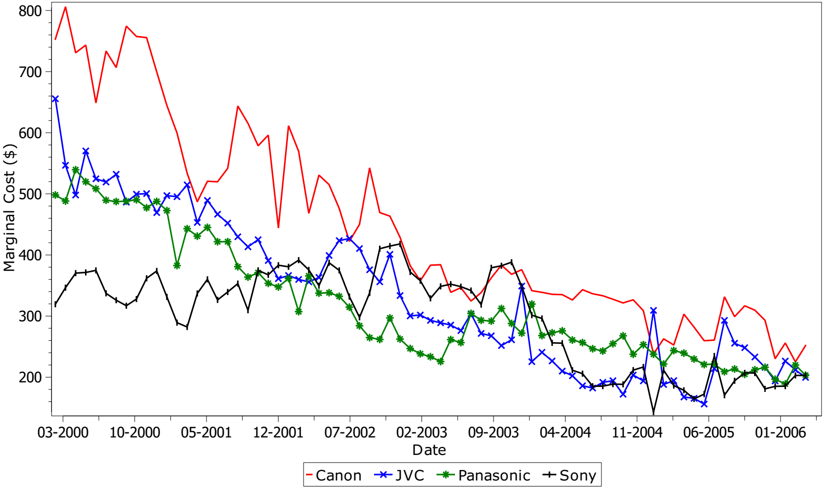
Results for Step 1

	Dependent variable: ln(price)			
	Firm Random Effect (1)		Firm Fixed Effect (2)	
Variable	Coefficient	Std.	Coefficient	Std.
Product quality	6.65***	(0.21)	6.62***	(0.1)
Firm average product quality	0.56	(0.65)	0.48	(0.33)
Firm size	0.013***	(0.002)	0.013***	(0.002)
Market average product quality	−2.8***	(0.95)	−2.66***	(0.94)
Market size	−0.003***	(0.001)	−0.003***	(0.001)
Consumer holdings	−9.61***	(0.25)	−9.6***	(0.3)
Constant	6.68***	(0.06)	6.18***	(0.06)
Observations	4,436		4,436	
Adjusted R^2	0.641		0.662	
Residual Std. Error	0.32		0.32	
F statistic			774.27*** ($df = 16; 4419$)	

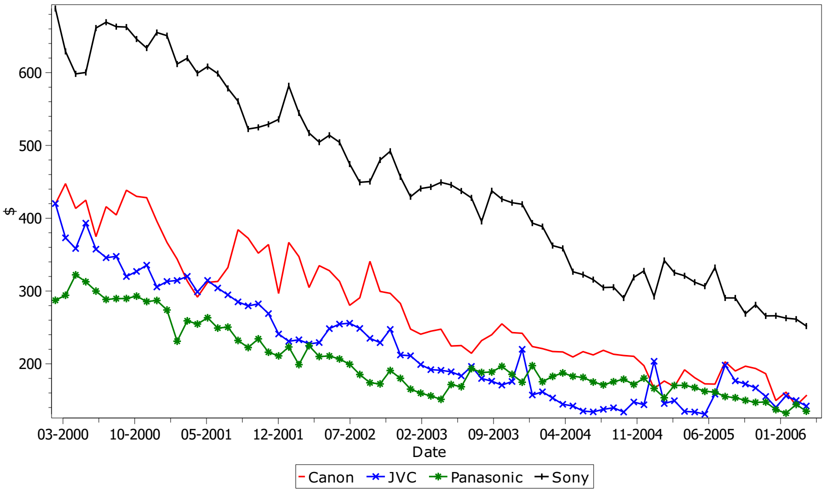
Step 2

- $T = 110$ (add 25 periods to data).
- $ns = 16$.
- $\beta = 0.99$.
- Discretize state space for δ_{it} into 100 values.
- Discretize state space for δ_{it}^{0} into 21 values.

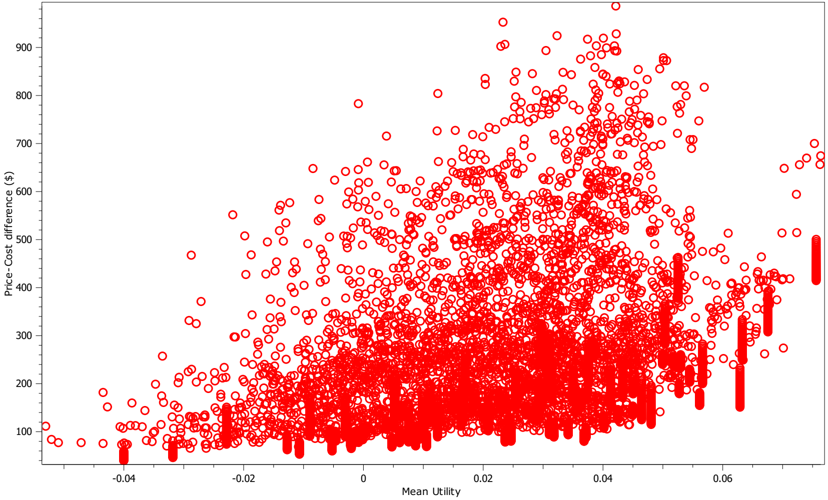
Average marginal cost by period and firm.



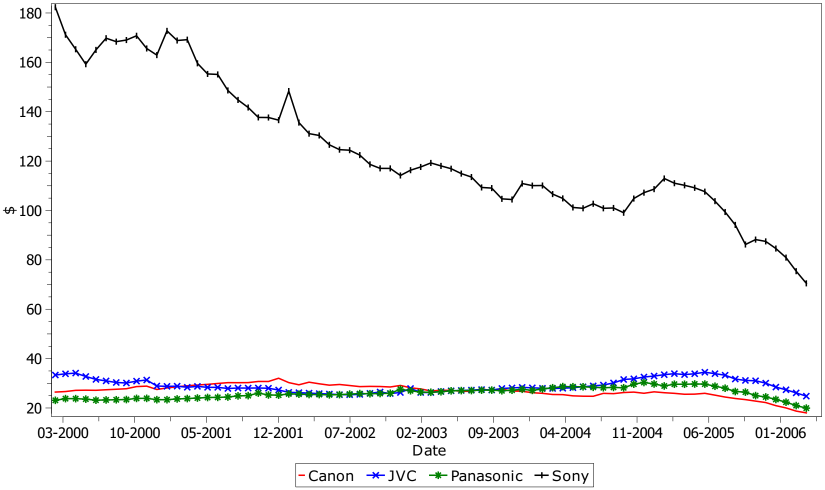
Average price-cost difference by period and firm.



Price-cost difference by flow utility.



Average difference between static and dynamic marginal costs.



Conclusion

- Dynamics affect computation of marginal cost
- Much more so for the biggest firm
- We have more work to do ...