A Dynamic Model of Margins in the LCD TV Industry

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Introduction

I study the relationship between *dynamic consumer behavior* and *prices* firms charge in equilibrium.

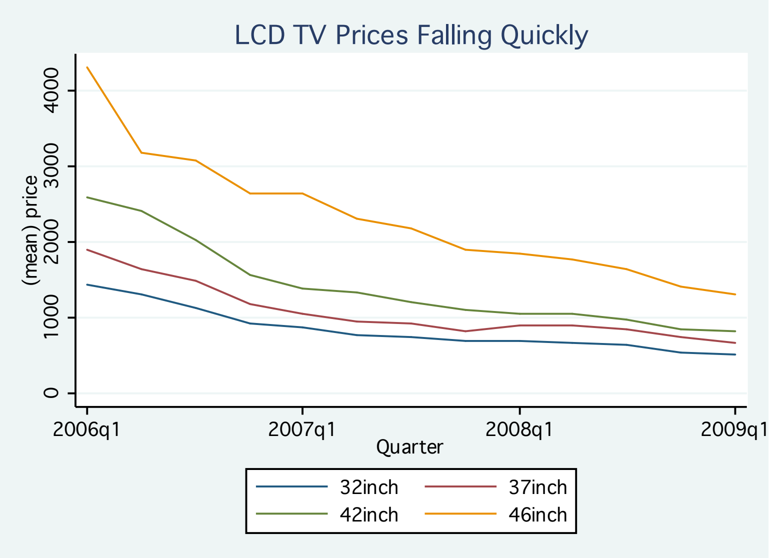
More specifically, I examine recent price declines in the market for LCD Televisions and the inter-temporal tradeoffs faced by consumers.

Coase Conjecture

This relates to an old literature on the Coase Conjecture, which says that durable goods monopolists may compete with themselves and have no market power.

- Firms "skim" by selling to high value consumers first.
- Consumers choose to purchase today or wait until the future.
- Consumers have a strategic option to delay.
- This limits firms' markups.

Price Declines in LCD TV's



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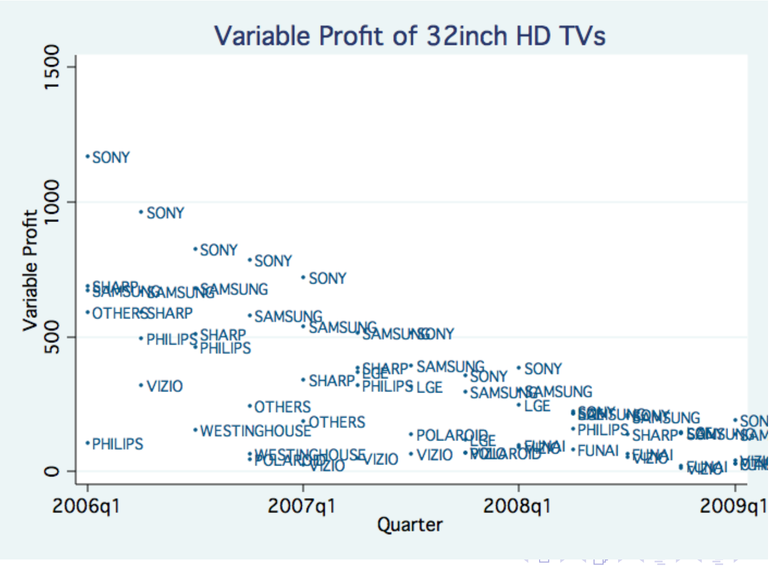

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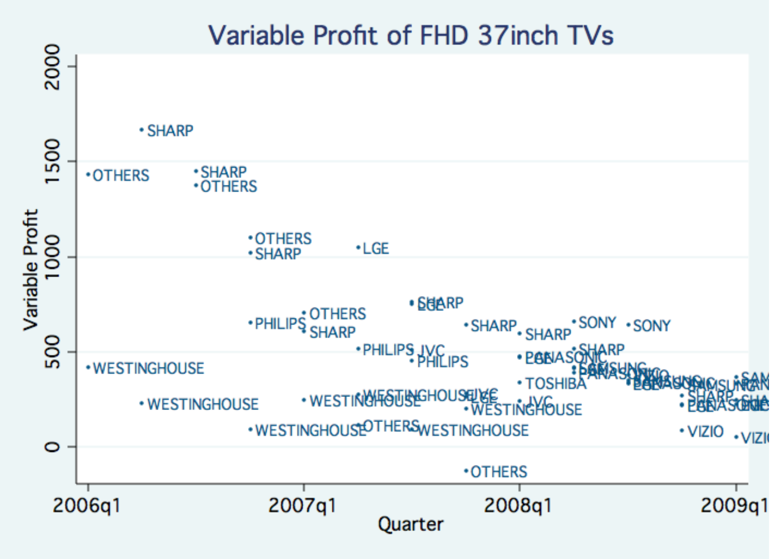

Reasons for Low Prices

There are four explanations for why prices might be low:

1. Costs are low
2. Competition
3. High value consumers have left the market
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These factors have different implications for:

1. Research & Development
2. Antitrust Policy

Literature

There is a large theoretical literature on these inter-temporal tradeoffs.

- Coase Conjecture: Coase (1972)
- Related literature Stokey (1982), Bulow (1982), etc.
- Theory literature mostly focuses on analytic results for single-product monopoly case

There is also a small but growing empirical literature (Adoption, Replacement, Stockpiling):

- Melnikov (2001), Carranza (2007), Zhao (2008), Lee(2008)
- Gowrisankaran & Rysman (2009)
- Nair (2007)
- Erdem, Imai, & Keane (2003), Hendel & Nevo (2007)

Outline

1. Write down a dynamic model of consumer behavior.
2. Estimate the model.
3. Recompute prices in the absence of an option to wait.
4. Recompute prices in when the distribution of consumers is fixed.

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This differs from past approaches in the literature in the following ways:

1. Focus on pricing problem not just demand side
2. Better data on manufacturer costs
3. Better computational technique (MPEC)
4. Improved statistical procedure (EL)

Model

Each consumer type is subscripted by i, and chooses a product j in period t to maximize utility:

$$
\begin{aligned}
u_{ijt} &= \alpha_i^x x_{jt} - \alpha_i^p p_{jt} + \xi_{jt} + \varepsilon_{ijt} \\
u_{i0t} &= \overline{u}_{i0t} + \varepsilon_{i0t}
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Consumers have a continuation value which depends on their existing television stock u_{i0t}.

$$\begin{aligned} V_i(u_{i0t}, \varepsilon_{it}, \Omega_t) &= \max\{u_{i0t} + \beta E[E_\varepsilon V_i(u_{i0t}, \varepsilon_{it}, \Omega_{t+1})|\Omega_t], \\ &\quad \max_j u_{ijt} + \beta E[E_\varepsilon V_i(u_{ijt}, \varepsilon_{it}, \Omega_{t+1})|\Omega_t]\} \end{aligned}$$

Assumptions

Assumption: No Upgrades

We rule out upgrades. After making a purchase consumers exit the market. $V_i(u_{ijt}, \cdot) = 0$ when $j \neq 0$.

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- Right assumption for the industry (multiple purchases, utility differences)
- Simplifies state space (don't keep track of TV stocks)
- Not necessary for estimation

Solving the Model

If ε_{ijt} is IID and Extreme Value, the model can be simplified. Note that the expected utility that i receives from making a purchase in period t does not depend on which product j is purchased.

$$\delta_{it} = E[\max_j u_{ijt}] = \log \sum_j \exp(x_{jt}\alpha_i^x - \alpha_i^p p_{jt} + \xi_{jt})$$

$$V_i(\Omega_t) = \int V_i(\varepsilon_{ijt}, \Omega_t) f(\varepsilon)$$

(Standard Abuse of Notation)

Solving the Model (2)

Now we can use Rust (1987) to simplify the dynamic stopping problem.

$$
\begin{aligned}
V_i(\varepsilon_{it}, \Omega_t) &= \max\{u_{i0t} + \beta E[E_\varepsilon V_i(\varepsilon_{it}, \Omega_{t+1})|\Omega_t], \max_j u_{ijt}\} \\
V_i(\Omega_t) &= \log\left(\exp(\beta E[V_i(\Omega_{t+1})|\Omega_t]) + \exp(\delta_{it})\right) + \eta
\end{aligned}
$$

Challenges

The key remaining challenge is that Ω_t is infinite dimensional.

Literature: IVS Assumption

The literature exploits the fact that $V_i(\Omega_t)$ recursively depends on itself and the inclusive value to assume that $\Omega_t = \delta_{it}$ and $P(\Omega_{t+1}|\Omega_t) = P(\delta_{i,t+1}|\delta_{it})$.

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- A common choice of functional form is that δ_{it} follows an AR(1).
- The problem with this is that it is not the result of economic behavior.

Assumption 2

I make a different assumption on the beliefs of consumers:

Perfect Foresight

$$
\begin{aligned}
v_{i,t+1} &= E[V_i(\Omega_{t+1})|\Omega_t]) \\
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This may be more reasonable than it seems:

- Consumers know future value of market exactly (not all characteristics of all products)
- Just deviation in utility of outside option
- Already have ε_{ijt} and ξ_{jt}.

Solving the Model (3)

Now we can write the purchase probabilities for type i

$$s_{ijt} = \frac{e^{\delta_{it}}}{e^{v_{it}}} \cdot \frac{e^{\beta_i x_{jt} - \alpha_i p_{jt} + \xi_{jt}}}{e^{\delta_{it}}}$$

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Each type has an associated weight w_{it} in each period. Consumers leave the market after making a purchase so that:

$$w_{i,t+1} = w_{i,t} s_{i0t}$$

Estimating Moment Condition Models

We estimate this model using the following moment condition:

$$E[\xi_{jt} Z_{jt}] = 0$$

- Typically we use GMM and minimize the quadratic distance between the moments of the model and the moments of the data.
- I consider an alternative approach based on Empirical Likelihood

Advantages of Empirical Likelihood

Empirical Likelihood Methods have a number of advantages over GMM:

- Higher-Order Efficient (better standard errors)
- Doesn't require a weighting matrix
- Simple likelihood units for testing

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The main drawback has essentially been computational.

The EL Estimator

The empirical likelihood estimator considers a set of weights ρ_{jt} and minimizes the NPMLE subject to the constraint that the moment conditions hold exactly.
For the demand problem this is:

$$\begin{aligned} L(\rho) &= \prod_{j,t} \rho_{jt} \rightarrow \sum_{j,t} \log \rho_{jt} \\ E[\xi_{jt} z_{jt}] &= \sum_{j,t} \rho_{j,t} \xi_{jt} Z_{jt} = 0 \\ \sum_{j,t} \rho_{jt} &= 1 \end{aligned}$$

The Dual EL Estimator

Most previous approaches have focused on the dual:

$$\hat{\theta}_{EL} = \arg\max_{\theta \in \Theta} l_{NP}(\theta) = \arg\max_{\theta \in \Theta} \min_{\gamma \in \mathbb{R}^q} -\sum_{i=1}^{n} \log(1 + \gamma' g(z_i, \theta))$$

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- Avoids finding n parameters for weights, instead just Lagrange multipliers on moments
- At the cost of making the problem MUCH more difficult

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- Unconstrained rather than constrained
- Avoids finding n parameters for weights, instead just Lagrange multipliers on moments
- At the cost of making the problem MUCH more difficult
- For each guess of θ we must find the optimal p (actually γ), but it may be that $\nexists p$ s.t $\sum_{i=1}^n p_i g(z_i, \theta) = 0$ at some θ.[1]
- Not much in terms of max min solvers (stuck with nested
- $\nabla_\theta \cdot l_{NP}(\theta) = \nabla_\theta \left[\min_{\gamma \in \mathbb{R}^q} - \sum_{i=1}^n \log(1 + \gamma' g(z_i, \theta))\right]$ hard

[1] $\{g(z_i, \theta)\}_{i=1}^n$ fail to span the origin of $\mathbb{R}^q$

The Estimation Problem

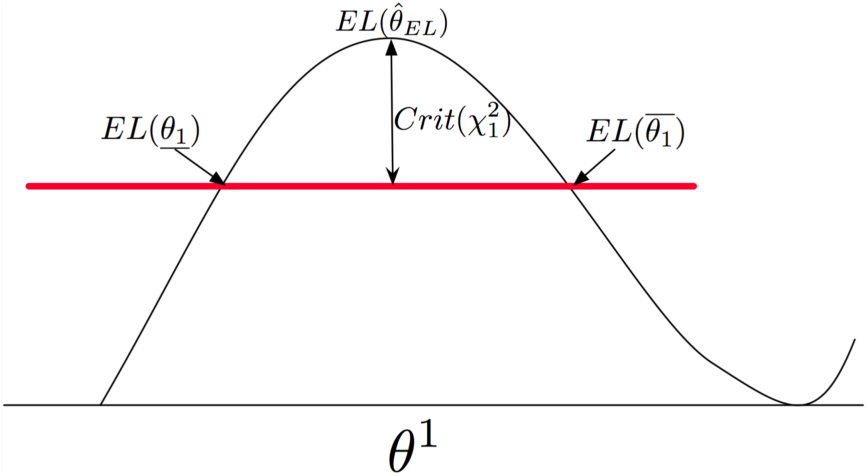
$$
\begin{aligned}
\max_{(\rho_{jt}, R_{it}, w_{it}, s_{ijt}, \delta_{it}, \xi_{jt}, \alpha_i)} \sum_{j,t} \log \rho_{j,t} \quad & \text{s.t.} \quad S_{jt} = s_{jt} \\
s_{ijt} &= \exp[x_{jt}\alpha_i^x - \alpha_i^p p_{jt} + \xi_{jt} - v_{it}] \\
s_{jt} &= \sum_i w_{i,t} s_{ijt} \\
w_{i,t+1} &= w_{i,t}(1 - \sum_j s_{ijt}) \\
\exp[\delta_{it}] &= \sum_j \exp[x_{jt}\alpha_i^x - \alpha_i^p p_{jt} + \xi_{jt}]) \\
v_{it} &= \log(\exp(\delta_{it}) + \exp(\beta v_{i,t+1})) \\
\sum_{\forall j,t} \rho_{jt}\xi_{jt} Z_{jt} &= 0 \quad \sum_{\forall j,t} \rho_{jt} = 1
\end{aligned}
$$

The MPEC Approach

Estimate via the MPEC approach of Judd and Su (2008)

- Solve the problem directly using constrained optimization
- Key is that constraints only need to hold at optimum
- Problem has a LOT of parameters
- Problem is nearly convex
- Problem is highly sparse
- Dynamics are NOT approximated

EL Inference



Description of Dataset

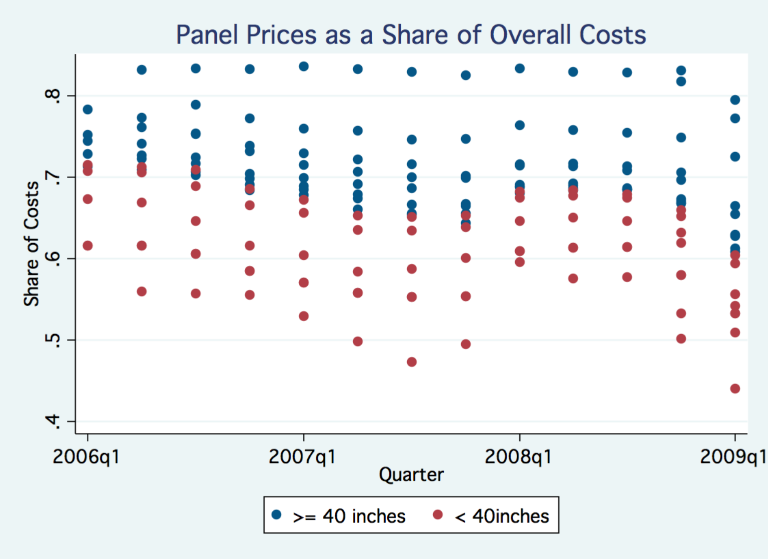
- I use data from NPD/DisplaySearch on LCD TV quarterly sales from 2006-2009 (13 quarters).
- The data track shipments from manufacturers to the USA.
- Retail prices are sales weighted and obtained from a number of retailers (Best-Buy, Circuit City, Costco, Target, etc.)
- The LCD TV industry has an unusual feature that 68% of costs and 86% of cost variation are from a single component (the panel)
- Panel prices are produced by separate firms with predictable technology and are well-tracked
- Other costs are obtained from NPD's quarterly teardown analysis

Cost Breakdown Example

Input	Q4 2007	Q1 2008
LCD Module Price in Previous Quarter	810.31	789.91
Inverter	0.00	0.00
NTSC Tuner	5.16	0.00
ATSC Tuner Demod	21.85	5.40
Image Processing	21.38	21.32
Audio Processing	10.30	8.60
Power	20.02	25.00
Other Electronics	29.83	28.48
PCB Mechanical	5.76	5.00
Other Mechanical	92.24	85.30
Packaging&Accessories	16.09	16.04
Royalties	10.00	10.00
Labor Overhead	62.58	59.70
Warranty for 12-18 Months	31.29	29.85
USA Import Duty	0.00	0.00
Freight to USA	6.52	6.46
Insurance	4.57	4.36
Handling & Surface	8.04	7.67
Ex-Hub	1155.92	1103.09

Table: Cost Breakdown Example: 46" FHD TV

Panel as a share of Input Costs



Demand Results

	Static	Dynamic
Price	-0.0034	-0.0293
HD	2.2521	1.8301
FHD	2.332	1.7834
Size/100	-0.0251	0.0282
$Size^2/1000$	-0.0006	-0.00019
Manuf	x	x
σ^p	0.0009	0.0051
σ^s	0.0116	0.00164
σ_{FHD}	0.0230	0.0921
EL	11467	10941

Simple Substitution Patterns

Suppose the price of a focal product increases by 10% in 2007 quarter 1. How do consumers respond?

	40" Vizio HD	46" Sony FHD
Buy Anyway	13%	30%
Same Product Tomorrow	16%	15%
Other Product Today	31%	26%
Other Product Tomorrow	40%	29%

Supply Side

- The goal is to understand how the consumer dynamics influence the prices firms charge
- Normally we have to back marginal costs out of a model.
- Instead those are obtained from additional data
- Want to recompute markups in some counterfactual scenarios and compare prices
- Fully dynamic pricing can be tricky
- Perfect foresight simplifies equilibrium.

Supply Side

The goal is to consider counterfactual pricing equilibria that account for:

1. Falling Costs
2. Changes in Competitive Environment
3. Changes in Consumer Valuations
4. Changes in Option Value

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Static Pricing

It is helpful to define the $J \times J$ matrix of same-brand price elasticities, where J_g represents the set of products owned by multi-product firm g.

$$A_{jk} = \frac{\partial s_{kt}}{\partial p_{j\tau}} \text{ when } (j,k) \in J_g, t = \tau \quad 0 \quad \text{o.w.}$$

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Assume there is a fixed population of consumers M, then firms choose a set of prices p_{jt} for products they own J_g in order to maximize profits by examining the FOC:

$$\begin{aligned}
\max_{p_{jt} \in J_g} \pi_{gt} &= \max_{p_j \in J_g} \sum_{j \in A_g} M(p_{jt} - c_{jt}) s_{jt}(\mathbf{p_t}, \theta) \\
\Rightarrow s_{jt} &= \sum_{k \in J_g} (p_{kt} - c_{kt}) \frac{\partial s_{kt}}{\partial p_{jt}} = A(\mathbf{p} - \mathbf{c}) \\
\Rightarrow \mathbf{p} &= \mathbf{c} + A^{-1} s(\mathbf{p}, \theta)
\end{aligned}$$

Dynamic Pricing

Firms, subscripted by g, now solve a more challenging problem where $\tilde{\sigma}$ is a state variable that contains information about the past history of prices and beliefs by firms and consumers about which strategy is being played.

$$V_g(\tilde{\sigma}_t) = \max_{p_{jt} \in A_g} E\pi_{gt}(\tilde{\sigma}_t, \mathbf{p_t}) + \beta_m \int V_g(\tilde{\sigma}_{t+1}) Pr(\tilde{\sigma}_{t+1} | \tilde{\sigma}_t, \mathbf{p_t})$$

If we know the set of consumer tastes and product quality $\theta = (\xi, \alpha_i)$, then demand is described in each period by (v_t, w_t). In the demand model, v_{it} is a sufficient statistic at time t for a consumer's beliefs about the future.

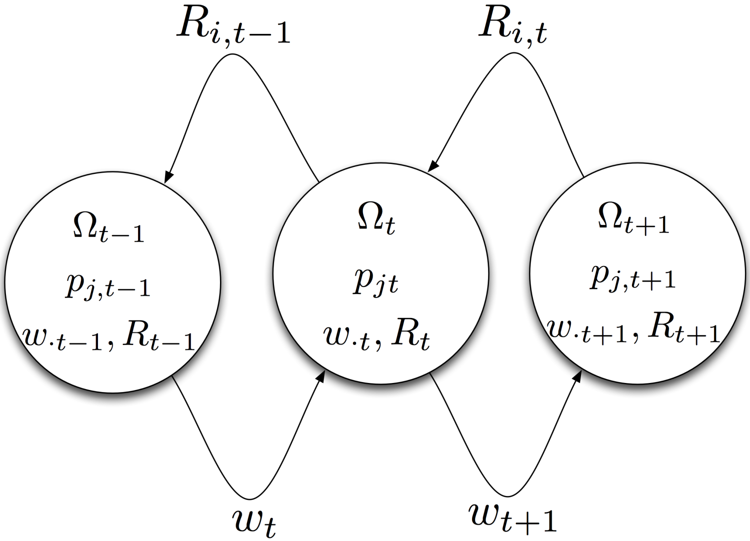
Assumptions

It helps to make the following assumptions:

- The state variable $\tilde{\sigma} = (v_t, w_t)$ depends on the two demand variables.
- Firms know everything about the future state of the industry (products, competitors, characteristics, ξ_{jt}) except prices

The idea is that firms price only based on the demand state, not actions or beliefs about actions of other firms.

Dynamic Pricing



Exercise 1: Myopic Firms

A simple exercise is to consider the case where firms are myopic and price as if each period will be their last. That is we set $\beta_m = 0$ and firms simply solve the static problem.

$$V_g(\tilde{\sigma}_t) = \max_{p_{jt} \in A_g} E\pi_{gt}(\tilde{\sigma}_t, \mathbf{p_t}) + \beta_m \int V_g(\tilde{\sigma}_{t+1}) Pr(\tilde{\sigma}_{t+1} | \tilde{\sigma}_t, \mathbf{p_t})$$

At the same time, consumers are not-myopic. That is the consumers anticipate this strategy and adjust their value of waiting appropriately.

$$\begin{aligned} \mathbf{p_t} &= \mathbf{c_t} + A_t(v_t, w_t)^{-1} s_t(\mathbf{p_t}, v_t, w_t, \theta) \\ w_{i,t+1} &= w_{i,t} s_{i0t} \\ v_{i,t} &= \ln\left(\exp(\delta_{it}(\mathbf{p_t}) + \exp(\beta v_{i,t+1})\right) \end{aligned}$$

Exercise 2: Myopic Consumers

Another simple exercise is to consider the case where consumers are myopic. That is consumers do not account for their option to wait when making a purchase, so that $E[v_{i,t+1}] = 0$

$$\begin{aligned} v_{i,t} &= \beta \ln\left(\exp(\delta_{it}(\mathbf{p_t}) + 1\right) \\ w_{i,t+1} &= w_{i,t} s_{i0t} \end{aligned}$$

The solution concept is subgame perfection. The demand state evolves in a simple deterministic way as consumers make purchases and leave the market.

$$V_g(w_t) = \max_{p_{jt} \in A_g} \pi_{gt}(w_t, v_t, \mathbf{p_t}) + \beta_m \int V_g(w_{t+1}(\mathbf{p_t}))$$

Exercise 3: No Change in Distribution of Consumers

This exercise considers the case where consumers may still delay their purchase of durable goods, but after making a purchase they are immediately replaced with a new consumer of the same type. That is:

$$\begin{aligned} v_{i,t} &= \beta \ln\left(\exp(\delta_{it}(\mathbf{p_t}) + \exp(v_{i,t+1})\right) \\ w_{i,t} &= w_{i,0} \quad \forall t \end{aligned}$$

The solution concept is subgame perfection, but now the demand state evolves in the opposite direction.

$$V_g(v_t) = \max_{p_{jt} \in A_g} \pi_{gt}(w_t, v_t, \mathbf{p_t}) + \frac{1}{\beta_m} \int V_g(v_{t-1}(\mathbf{p_t}))$$

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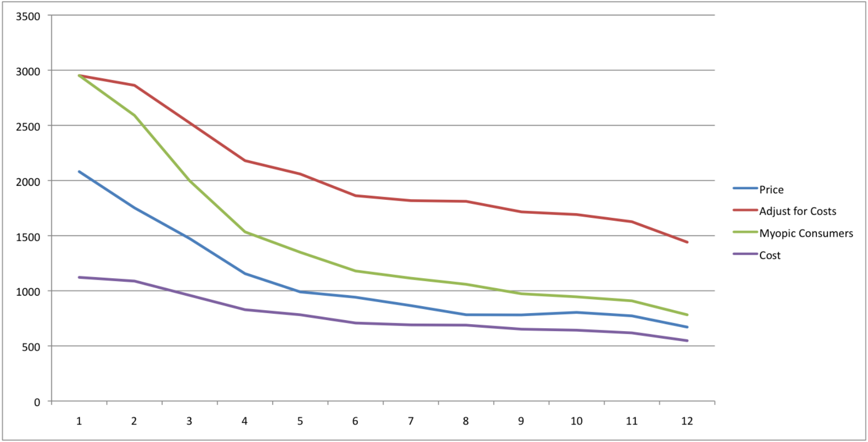

Anaylsis

- The factor that influences price the most appears to be changes in the distribution of consumers over time. This would lead to prices that would be 35% to 50% higher than the ones observed in the marketplace
- If consumers were myopic this would have a strong effect on periods where cost declines were large (close to 10%) but little to no effect when costs declines were small (about 3%).
- Myopic firm pricing strategies do not appear to be much different from the prices observed in the marketplace.
- Importance of oligopolistic competition.

Lessons for firms

Firms struggle to make money in this industry:

- Try to introduce valuable new characteristics (120/240Hz, Slim, LED)
- New characteristic of 2010: 3D
- What drives adoption?

Conclusion

- Cost and competitive landscape are important
- Which consumers firms sell to appears to dictate prices.
- Consumer's value of waiting is not as important