Dynamics of Consumer Demand with Aggregate Data

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Introduction

- Estimating demand is central to research in industrial organization.
- And comes up frequently in every field of economics.
- And problem is often dynamic!
  - Durable goods, storable goods, subscription goods, performance goods
- Most dynamic methods are designed for *disaggregate data*
  - Survey or household level data, often panel.
- Focus of today: *Aggregate data*
  - e.g., Quantity of product sold.
  - Cannot match household characteristics to products or product characteristics.

Sources of Dynamics

- Durable goods
  - e.g., cars, consumer electronics, appliances.
  - See Schiraldi (2011), Gowrisankaran & Rysman (2012).
- Storable goods
  - e.g., laundry detergent, packaged food.
  - See Hendel & Nevo (2006).
- Subscription services
  - e.g., bank accounts, insurance plans, memberships.
  - See Shcherbakov (2016), Ho (2015).
- Performance goods
  - e.g., Live theater and music, museum exhibits, books, movies.
  - See Ho, Rysman & Wang (2025)

Aggregate vs disaggregate data

Disaggregate:

- Can match HH chars to product chars.
- Can track HH changes over time.
  - Important for studying upgrading or switching.
- Can observe HH outside option.
- Can observe transaction price.
- Address price endogeneity with product fixed effects.

Aggregate:

- Often all that is available.
- Often necessary to study supply side.
- Address endogeneity with IV methods.

Static demand for aggregate data

- Leading model: Berry, Levinsohn & Pakes (1995).
- Highlights importance of accounting for unobserved consumer heterogeneity in generating realistic results.
- Our approach: Apply dynamics to BLP model.
- Combine Rust (1987) with Berry et al. (1995).
- Allow for *persistent unobserved heterogeneity* in consumer preferences.
- Make use of methods to combine aggregate and disaggregate data.

Background: BLP 1995

Static demand

Products

- There J products available, $j = 1, \ldots, J$.
- Products are characterized by a vector of L observable characteristics: x_j.
  - e.g., For cars, x_j may contain size, cost per mile, safety features.
- Also price p_j and 1 unobservable characteristic ξ_j.

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Consumers

- Continuum of consumers i.
- Have preferences for product characteristics ν_i $(L \times 1)$
  - $\nu_i \sim G$
- Pick 1 product or outside option $j = 0$.

BLP demand

- Let utility to consumer i from purchasing product j be:

$$u_{ij} = x_j \alpha^x - \alpha^p p_j + \sum_{l=1}^{L} x_{jl} \nu_{il} \sigma_l + \xi_j + \varepsilon_{ij}$$

  - Estimate $\theta = \{\alpha^x, \alpha^p, \sigma_l\}$.
  - x_{jl} and ν_{il} captures match between i and j due to characteristic l.
  - ε_{ij} is distributed EV.
- Assume $u_{i0} = \varepsilon_{i0}$

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- Assume $u_{i0} = \varepsilon_{i0}$
- In practice, let $F_j = x_j\alpha^x - \alpha^p p_j + \xi_j$, so:

$$u_{ij} = F_j + \sum_{l=1}^{L} x_{jl}\nu_{il}\sigma_l + \varepsilon_{ij}$$

Market shares

- EV assumption implies closed form solution for share of i that picks j:

$$s_{ij}(\nu_i, \boldsymbol{F}, \theta) = \frac{\exp\left(F_j + \sum_{l=1}^{L} x_{jl}\nu_{il}\sigma_l\right)}{1 + \sum_{k=1}^{J} \exp\left(F_j + \sum_{l=1}^{L} x_{kl}\nu_{ik}\sigma_l +\right)}.$$

- But we observe only share for product j:

$$s_j(\theta, \boldsymbol{F}) = \int_{\nu_i} s_{ij}(\nu_i, \boldsymbol{F}, \theta) g(\nu_i) d\nu_i.$$

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No closed form solution

Use numerical integration

Getting mean utiliy

- Berry (1994) shows that F_j is invertible from market shares in this model.
- We want to find F_j that generates observed shares.
- No analytic solution.

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- We want to find F_j that generates observed shares.
- No analytic solution.
- Use *fixed point equation*

$$F_j' = F_j + \ln(s_j^*) - \ln(s_j(\boldsymbol{F}, \theta)).$$

Algorithm

1. Draw $L \times 1$ vector ν_{il} from normal S times.
2. Guess θ
3. Guess $\boldsymbol{\delta}$.
4. Calculate $s_{ij}(\nu_i, \boldsymbol{F}, \theta)$.
5. Calculate $s_j(\boldsymbol{F}, \theta) = \frac{1}{S} \sum_{i=1}^{S} s_{ij}(\nu_i, \boldsymbol{F}, \theta)$.
6. Calculate $F_j'(\theta) = F_j(\theta) + \ln(s_j^*) - \ln(s_j(\boldsymbol{F}, \theta))$.
7. If $d(\boldsymbol{F}', \boldsymbol{F}) > \texttt{tol}$, let $\boldsymbol{F} = \boldsymbol{F}'$ and go to 4.
8. Let $\xi_j(\theta) = \delta_j - x_j\alpha^x - \alpha^p p_j$.
9. Form moments $m(\theta) = \boldsymbol{Z}'\xi(\theta)$.
10. Form GMM objective function $m(\theta)' W m(\theta)$. Get new θ'. Go to 3.

Takeaways

- Random coefficients in logit utility allow for much more realistic substitution patterns.
- Model leads to *nested fixed point algorithm* to obtain error term in non-linear model.

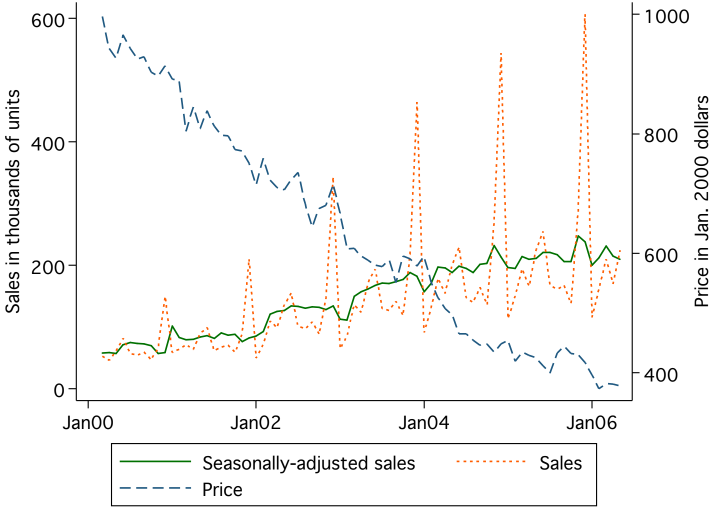
Variation in data (loosely):

- If share s_j increases when x_{jl} increases, α_l must be large.
- If it takes share from nearby in x space, σ must be large.

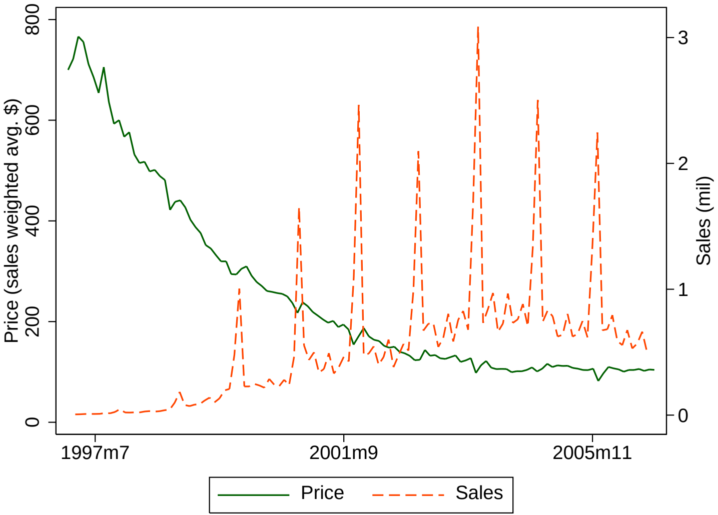
Adding dynamics: Consumer electronics

- Purchasing consumer electronics is a dynamic decision.
  - Prices fall over time.
  - Quality, variety increase over time.

Price and sales for digital camcorders



Price and sales for DVD players



Our Goal

- Estimate a structural model of consumer demand in the context of dynamics.
- Present applications of our model.

Literature

- Many papers address environments in which dynamics might be important.
- Almost all use static models of demand.
- Some important exceptions:
  - Gandal, Kende and Rob.
  - Esteban and Shum.
  - Melnikov (2001).
  - Carranza (2005), Gordon (2005), Nair (2004), Chintagunta and Song (2003), Santugini (2006).
- More work on disaggregate data:
  - Hendel and Nevo (2004), Erdem and Keane (1996), Hartmann (2005), Ackerberg.

Our model should have

- Persistent heterogeneous consumers.
- Dynamic decision making.
- Can be applied to aggregate data.

  Based on Gowrisankaran & Rysman (2012)

Sample no-purchase matrix

		Time			
		0	1	2	3
Type	*Hi*	1	0.9	0.8	0.7
		1	0.92	0.84	0.76
		1	0.94	0.88	0.82
	Lo	1	0.96	0.92	0.90

Consumer Model

- Discrete time t, infinite horizons.
- Continuum of heterogenous consumers i.
- J_t products are available in t.
  - Infinitely durable.
- Repurchase replaces old good with new.

Consumer Model

Consumer i buying good j at time t pays p_{jt} gets utility flow at time $\tau \geq t$:

$$u_{ijt} = \overbrace{x_j \alpha_i^x + \xi_{jt}}^{f_{ijt}} - \alpha_p^i p_{jt} + \epsilon_{ijt}.$$

- x_j is product characteristics.
- ξ_{jt} is unobserved characteristic.
- $\epsilon_{ijt} \sim$ Extreme Value.
- Receive flow f_{ijt} until repurchase.
- Flow utility for no purchase: $u_{i0t} = \epsilon_{i0t}$.

Dynamics of consumer model

Bellman equation

$$V_i(f_0, \Omega, \epsilon_i) = \max_{j=0,\dots,J} \left\{ f_{ij} + \epsilon_{ij} + \beta E_i \left[V_i(f_{ij}, \Omega', \epsilon_i') | \Omega \right], \right.$$

$$\left. f_0 + \epsilon_{i0} + \beta E_i \left[V_i(f_0, \Omega', \epsilon_i') | \Omega \right] \right\}.$$

- $\Omega = \{x_j, p_j, \xi_j\} \forall j \in J \ \cup$ `Consumer holdings.`

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- $\Omega = \{x_j, p_j, \xi_j\} \forall j \in J \quad \cup \quad \texttt{Consumer holdings.}$
- Integrate out ϵ_i.

$$EV_i(f_0, \Omega) = \int_{\epsilon_i} V_i(f_0, \Omega, \epsilon_i) dP_{\epsilon_i}.$$

Simplify the state space

Define the inclusive value *of purchase* for i:

$$\delta_i(\Omega) = \ln \left(\sum_{j \in J} \exp\left(f_{ij} - \alpha_i p_j + \beta E[EV_i(f_j, \Omega') | f_j, \Omega] \right) \right) .$$

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$$\delta_i(\Omega) = \ln\left(\sum_{j\in J}\exp\left(f_{ij} - \alpha_i p_j + \beta E[EV_i(f_j,\Omega')|f_j,\Omega]\right)\right).$$

- In deciding the value of waiting, consumers care only about the sequence of δ_i, not otherwise about Ω.

$$EV_i\left(f_0,\Omega\right) = EV_i\left(f_0,\delta_i,P\left[\delta_i',\delta_i'',\delta_i''',\ldots|\Omega\right]\right)$$

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$$EV_i\left(f_0, \Omega\right) = EV_i\left(f_0, \delta_i, P\left[\delta_i', \delta_i'', \delta_i''', \ldots |\Omega\right]\right)$$

- Consumers still use Ω for predictions of δ_i.

$$EV_i(f_0, \Omega) = \ln\left(\exp(f_0 + \beta E[EV(f_0, \Omega')|f_0, \Omega]) + \exp(\delta_i(\Omega))\right).$$

Inclusive Value Sufficiency

Assumption: Inclusive Value Sufficiency (IVS)

If $\delta_i(\Omega) = \delta_i(\hat{\Omega})$, then $P(\delta_i(\Omega')|\Omega) = P\left(\delta_i(\hat{\Omega}')|\hat{\Omega}'\right)$ for all Ω, $\hat{\Omega}$.

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- Implies: 2-scalar state space.

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- Bellman equation:

$$EV_i(f_0, \delta_i) = \ln\left(\exp(f_0 + \beta E[EV(f_0, \delta')|f_0, \delta]) + \exp(\delta_i)\right).$$

Implementing IVS

- We specify an AR1 for $\delta_{it} = \delta_i(\Omega_t)$:

$$\delta_{it+1} = \gamma_{i1} + \gamma_{i2}\delta_{it} + \eta_{it}$$

  and we assume consumers know $\gamma_{i1}, \gamma_{i2}, \sigma_\eta$.
- Imposes rational expectations (conditional on functional form restrictions).
- Consumers expect market to asymptote: Stationarity.

Criticism I

- No oligopoly model justifies AR1 functional form.
- We try robustness checks
  - adding J_t as a state
  - Adding month effects
  - Perfect foresight
- We also do some specification tests,
- And some Monte Carlos.

Criticism II

- We are making an assumption on endogenous behavior, because δ_{it} incorporates future choices.
- An alternative (based on Hendel and Nevo, 2006):
- Assume that consumers do not track quality, but rather just an indicator for having the good.

$$\delta_i(\Omega) = \ln\left(\sum_{j\in J} \exp\left(f_{ij} - \alpha_i p_j + \beta E[EV_i(I,\Omega')|I,\Omega]\right)\right)$$

$$\delta_i(\Omega) = \ln\left(\sum_{j\in J} \exp\left(f_{ij} - \alpha_i p_j\right)\right) + \beta E[EV_i(I,\Omega')|I,\Omega]$$

Criticism II

$$\delta_i(\Omega) = \ln\left(\sum_{j\in J} \exp\left(f_{ij} - \alpha_i p_j\right)\right) + \beta E[EV_i(I,\Omega')|I,\Omega]$$

- Define flow $\delta_i^f(\Omega)$:

$$\delta_i^f(\Omega) = \ln\left(\sum_{j\in J} \exp\left(f_{ij} - \alpha_i p_j\right)\right)$$

- You can make the IVS assumption on δ_i^f rather than δ_i.
- Implies Bellman is:

$$\begin{aligned} EV_i(f_0, \delta_i^f) = \ln \exp(&f_0 + \beta E[EV(f_0, \delta_i^{f\prime})|f_0, \delta_i^f]) \\ &+ \exp(\delta_i^f + E[EV(f_0', \delta_i^{f\prime})|f_0, \delta_i^f]) \end{aligned}$$

Issues

Tradeoff:

IVS on flow utilities is more attractive, but product choice has no dynamic content.

- Tradeoff is not economic vs. computational.
- It is economic vs. economic.

Estimation overview

- Parameters to estimate $\lambda = \{\alpha, \Sigma\}$.
- Simulate heterogeneous consumers.
- For each set of parameters, find the vector of product utilities that rationalizes the observed market shares.
- Each vector of utilities implies a solution to the Bellman equation for each consumer draw.
- Solve BLP and Rust fixed point equations simultaneously.
- Regress utilities on product characteristics to construct a GMM objective function.

Estimation 1

For a given set of parameters and draws ν_i.

- Guess F_{jt}, δ_{it}, $EV(f_0, \delta_{it})$.
- Compute $f_{ijt} = F_{jt} + x_j \sigma_j \nu_i - p_j(\alpha^p + \sigma_p \nu_p)$.
- Compute
$$\delta_{it} = \ln \left(\sum_{j=1}^{J_t} \exp \left(f_{ijt} + \beta E_i \left[EV_i \left(f_{ijt}, \delta_{it+1} \right) \middle| \delta_{it} \right] \right) \right).$$
- Estimate AR1 for each i.
- Use γ to construct a transition matrix for discretized δ_{it}.
- Solve for value function (Rust 1987 fpa):
$$EV_i(f_0, \delta_i) = \ln \left(e^{\delta_i} + e^{f_0 + \beta E_i [EV_i(f_0, \delta'_{it}) | \delta_i]} \right).$$

Estimation 2

Purchase probabilities conditional on current product:

$$P_{it}(f_0) = \frac{e^{\delta_{it}}}{e^{\delta_{it}} + e^{f_0 + \beta E_i[EV_i(f_0, \delta_{it+1}) | \delta_{it}]}} \qquad P_{ij|t} = \frac{e^{f_{ijt} + \beta E_i\left[EV_i\left(f_{jt}, \delta_{it+1} \right) | \delta_{it} \right]}}{\sum_{k \in J_t} e^{f_{ikt} + \beta E_i[EV_i(f_{kt}, \delta_{it+1}) | \delta_{it}]}}.$$

Shares among *original* populations:

$$\hat{s}_{jt}\left(\xi, \Omega_t, \alpha, \Sigma, \beta\right) = \int_\alpha \int_{f_0} \hat{s}_{it}\left(f_0, \delta_{it}\right) \hat{s}_{ij|t}\left(\Omega_t\right) dP_{\alpha t}\left(f_0\right) dP\left(\alpha\right).$$

BLP fixed point equation:

$$F'_{jt} = F_{jt} + \ln(s_{jt}) - \ln(\hat{s}_{jt}).$$

Now begin algorithm again until convergence of F_{jt}, δ_{it} and EV_i.

Estimation 3

- Compute econometric errors:

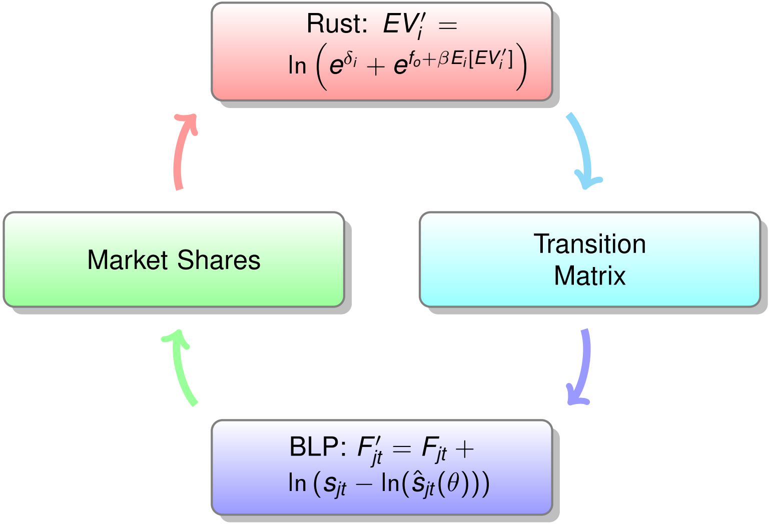
$$\xi_{jt} = F_{jt} - x_j \alpha^x.$$

- No proof of uniqueness!
- Pick α and σ to minimize GMM criteria function:

$$\xi_{jt}' \boldsymbol{Z} W \boldsymbol{Z}' \xi_{jt}.$$

  - z is instrument matrix
  - W is a weighting matrix.

Overview of method



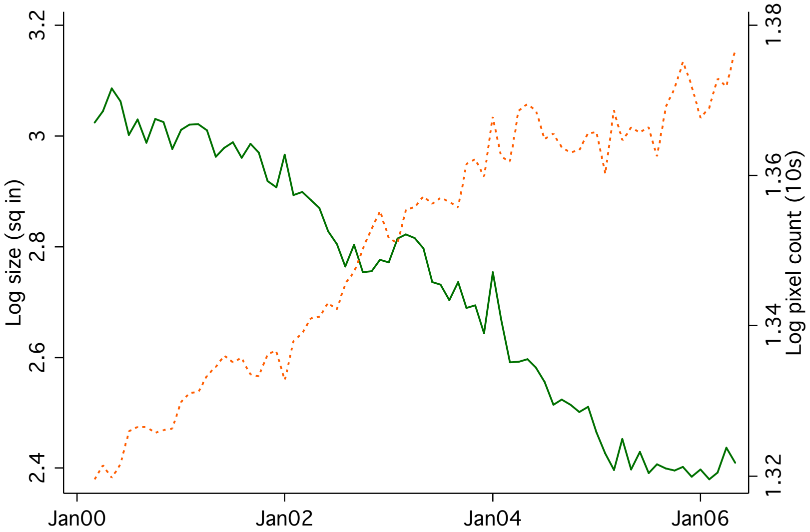
Identification

- Price drop at j leads to higher market share for j
- Amount of increase identifies mean of parameter
- Market share losers identifies variance
  - Only nearby products implies large variance
  - Spread across all products implies small variance
- Our model allows for substitution both within and across time periods

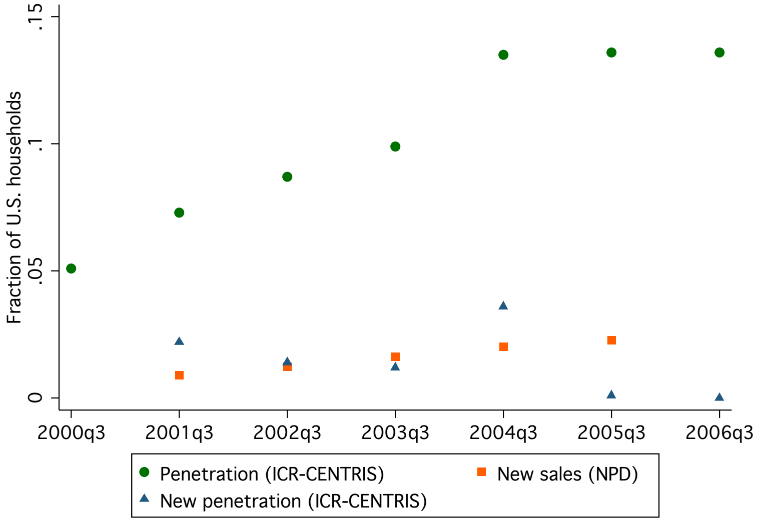
Data

- Digital camcorders
  - Monthly, March 2000 - May 2006.
  - 378 models, 11 brands, 4436 obs.
  - quantity, average price, characteristics.

Increasing quality for digital camcorders



Digital camcorder penetration



Make use of penetration data

- How can we make use of survey data?
- Construct moments from our model to match to data!
- In BLP literature, called *micromoments*

$$m^{\texttt{micro}}(\theta) = E[\texttt{Share purchased}]^* - E[\texttt{Share purchased}|\theta]$$

Make use of penetration data

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- Construct moments from our model to match to data!
- In BLP literature, called *micromoments*

$$m^{\texttt{micro}}(\theta) = E[\texttt{Share purchased}]^* - E[\texttt{Share purchased}|\theta]$$

- Stack with other moments:

$$m(\theta) = \begin{bmatrix} \boldsymbol{Z}\xi(\theta) \\ m^{\texttt{micro}}(\theta) \end{bmatrix}$$

Results

Parameter	Base dynamic model	Dynamic model without repurchases	Static model	Dynamic model with micro-moment
	(1)	(2)	(3)	(4)
Mean coefficients (α)				
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	.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) *
Media: tape	.012 (.005) *	-.005 (.683)	-.667 (.318) *	.015 (.018)
Media: HD	.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 (1147)	.087 (.038) *
Log price	.345 (.115) *	.001 (1.94)	-.001 (427)	.820 (.084) *

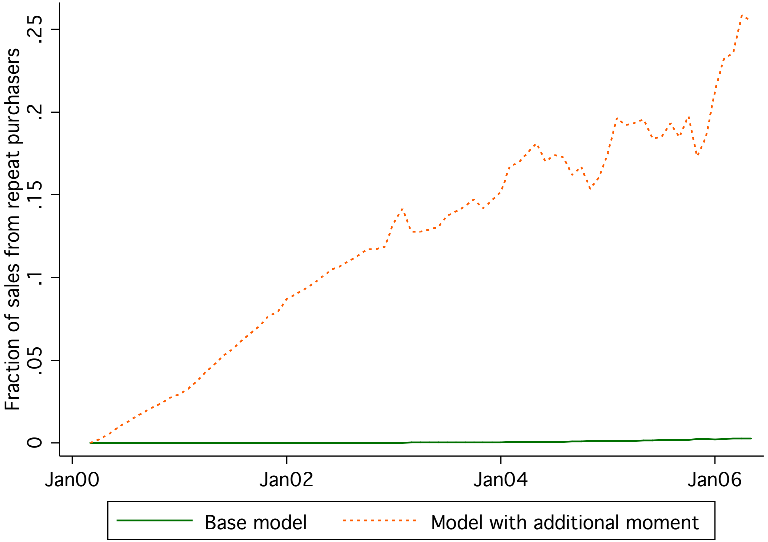
Standard errors in parentheses; statistical significance at 5% level indicated with *. All models include brand dummies, with Sony excluded. There are 4436 observations.

Results II

Parameter	State space includes number of products	Perfect foresight	Dynamic model with extra random coefficients	Linear price	Static model aggregated to year	Melnikov's model	Month dummies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean coefficients (α)							
Constant	-.098 (.026) *	-.129 (.108)	-.103 (.037) *	-.170 (.149)	2.26 (2325)	-6.61 (.815) *	-.114 (.024) *
Log price	-3.31 (1.04) *	-2.53 (.940) *	-3.01 (.717) *	-6.94 (.822) *	-.304 (38.0)	-.189 (.079) *	-3.06 (.678) *
Log size	-.007 (.001) *	-.006 (.001) *	-.015 (.007) *	.057 (.008) *	.653 (.234) *	-.175 (.049) *	-.007 (.001) *
Log pixel	.010 (.003) *	.008 (.001) *	.009 (.002) *	.037 (.012) *	-.863 (.822)	-.288 (.053) *	.010 (.002) *
Log zoom	.005 (.002) *	.004 (.002) *	.004 (.002)	-.117 (.012) *	-.779 (.455)	.609 (.074) *	.005 (.002)*
Log LCD size	.004 (.002) *	.004 (.001) *	.004 (.002) *	.098 (.010) *	-.283 (.626)	-.064 (.088)	.003 (.001) *
Media: DVD	.033 (.006) *	.025 (.004) *	.044 (.018) *	.211 (.053) *	.744 (2.02) *	.147 (.332)	.031 (.005) *
Media: tape	.013 (.005) *	.010 (.004) *	.024 (.016)	.200 (.051) *	.268 (1.43)	-.632 (.318) *	.012 (.004) *
Media: HD	.036 (.009) *	.026 (.005) *	.047 (.019) *	.349 (.063) *	.406 (2.63) *	-.545 (.419)	.034 (.007) *
Lamp	.005 (.002) *	.003 (.001) *	.005 (.002) *	.077 (.011) *	-.925 (.579)	-.200 (.058) *	.004 (.001) *
Night shot	.003 (.001) *	.004 (.001) *	.003 (.001) *	-.062 (.008) *	.855 (.275) *	.427 (.058) *	.003 (.001) *
Photo capable	-.007 (.002) *	-.005 (.002) *	-.007 (.002) *	-.061 (.019) *	4.41 (1.71) *	-.189 (.142)	-.007 (.008)
Standard deviation coefficients ($\Sigma^{1/2}$)							
Constant	.085 (.019) *	.130 (.098)	.081 (.025) *	.022 (.004) *	.027 (6800)		.087 (.013) *
Log price	.349 (.108) *	2.41e-9 (.919)	1.06e-7 (.522)	1.68 (.319) *	-.006 (131)		.287 (.078) *
Log size			-.011 (.007)				
Log pixel			1.58e-10 (.002)				

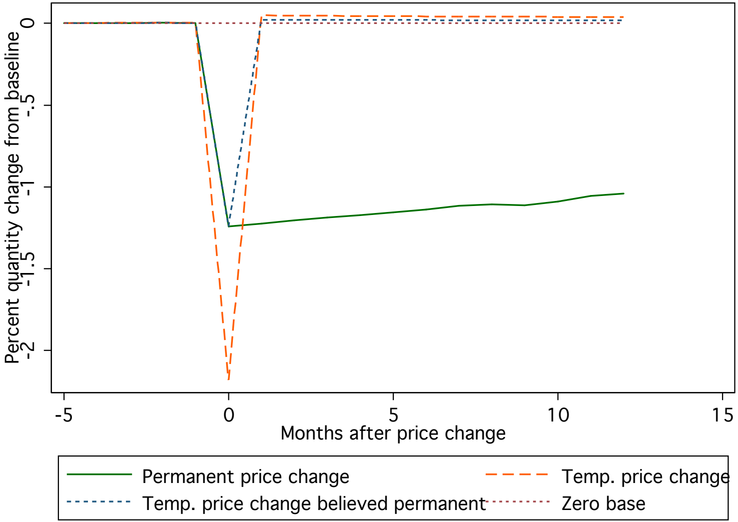
Standard errors in parentheses; statistical significance at 5% level indicated with *. All models include brand dummies, with Sony excluded. There are 4436 observations, except in the yearly model, in which there are 505.

Upgrading



Fraction of sales from repeat purchasers
0
.05
.1
.15
.2
.25
Jan00
Jan02
Jan04
Jan06
Base model
Model with additional moment

Industry dynamic price elasticities



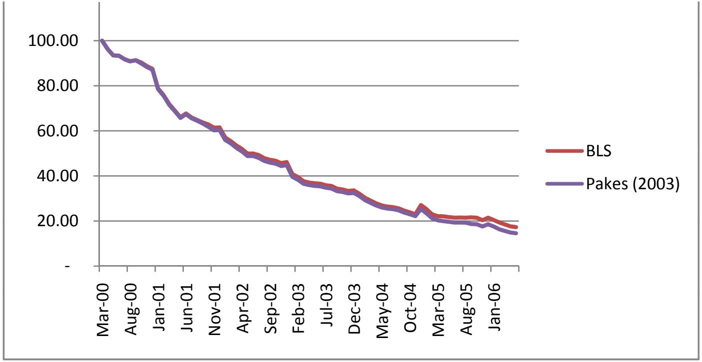
Welfare: Our implementation of the BLS approach

- BLS:

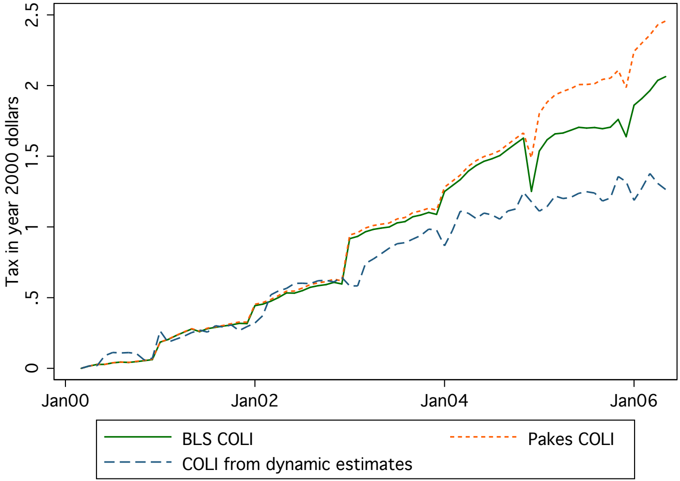
$$\frac{I_{t+1}}{I_t} = \sum_{j=0}^{J_t} s_{jt} \frac{p_{jt+1}}{p_{jt}}.$$

- Make assumptions about unobserved prices (due to entry and exit).
  - For instance, use average price (BLS), or predicted price from a regression on characteristics (Pakes, 2003).
- New Buyer Problem recognizes that changing buyers over time can make this problematic.

Standard Price Indices



Changes in Cost-of-Living



Results from COLI exercise

- BLS computes the income change necessary to allow a HH to buy a constant quality camcorder in each period.
- We compute the income change necessary to hold utility constant.

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Results from COLI exercise

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- We compute the income change necessary to hold utility constant.
- These diverge because as HH's accumulate the good, they value a new one less.
- Level differences are somewhat arbitrary, but shape differences are important.
- BLS price index continues to drop because prices do, whereas ours recognizes that later buyers are lower value.

Conclusion

- Integrate heterogeneous demand into a dynamic model with unobserved persistence.
- Leads to multiple fixed point algorithms
- But allows us to take important and challenging problems.

Price-cost margins in a dynamic environment

Why should we compute marginal cost?

- Compute price-cost margins.
  - Analyze market power.
- Run counterfactual experiments in oligopoly markets.
  - Example: merger simulation.

Standard approach.

- We typically cannot observe marginal cost.
- Compute MC by assuming it is equal to MR.
  - Berry, Levinsohn and Pakes.
  - Merger simulation.
- How should we proceed in a dynamic environment?
- In particular, digital camcorders, which are durable.

With dynamics:

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- It incorporates the change in current market share AND the change in the future stream of profits.

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- 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 decisions.

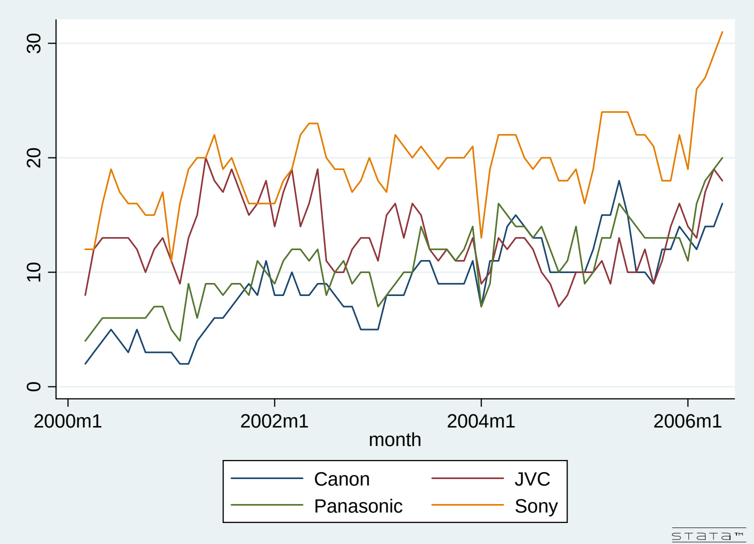
Our approach.

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

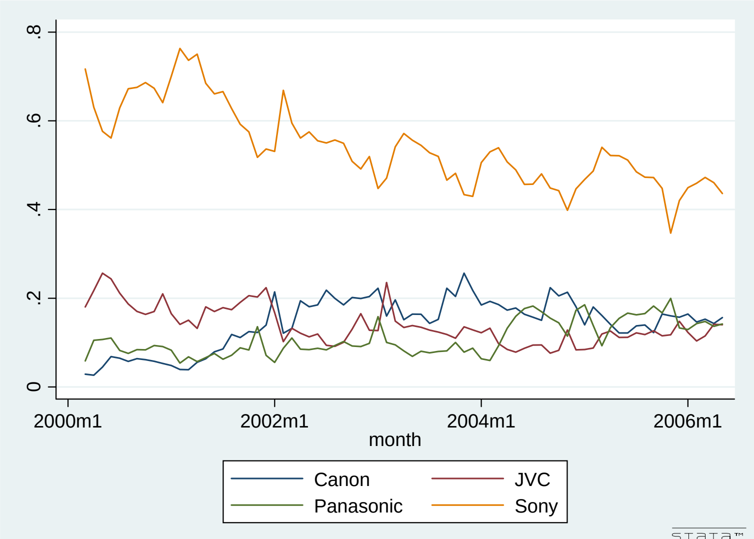
Step 2 Construct dynamic FOC and invert to compute MC. (BLP)

- Assume there is a final period, and proceed by backwards induction.
- Compute current market share and expected future profits.
- Change one price by 5%, and recompute.
  - Use Step 1 result to predict prices in the future.
- Use change in market share and the change in expected future profits to construct a first-order condition.
- Compute marginal cost that satisfies FOC.

Number of models, “Big 4" firms.



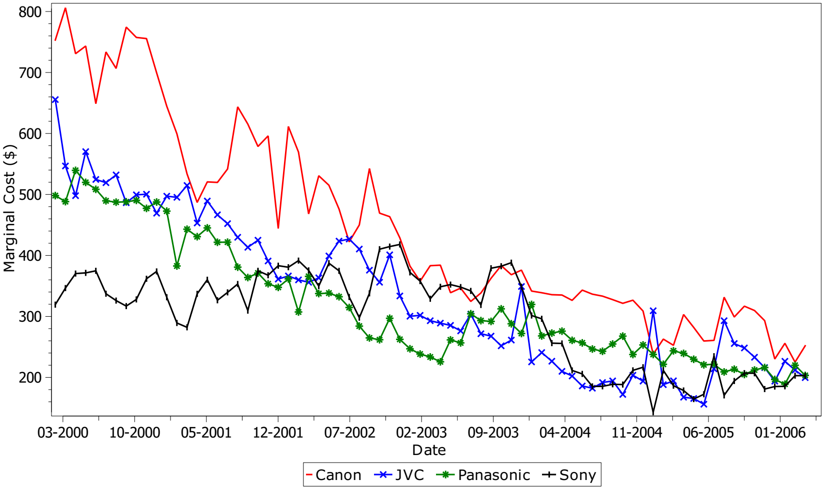
Market share over time, “Big 4" firms.



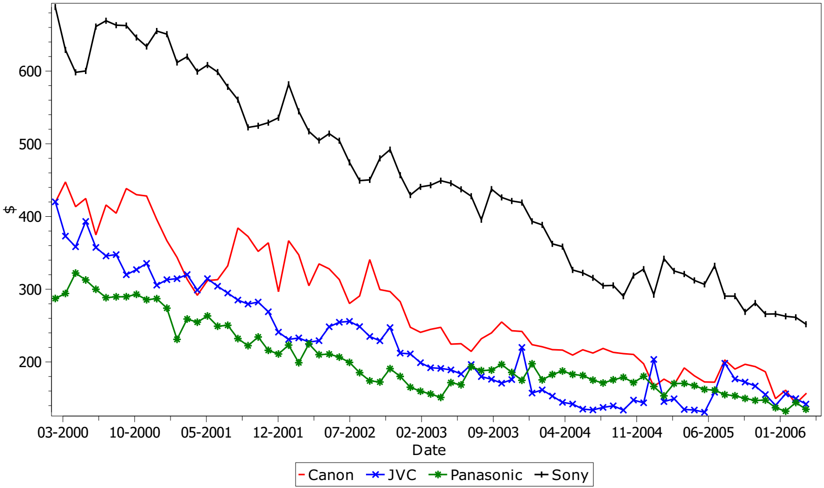
Results for Step 1

	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)

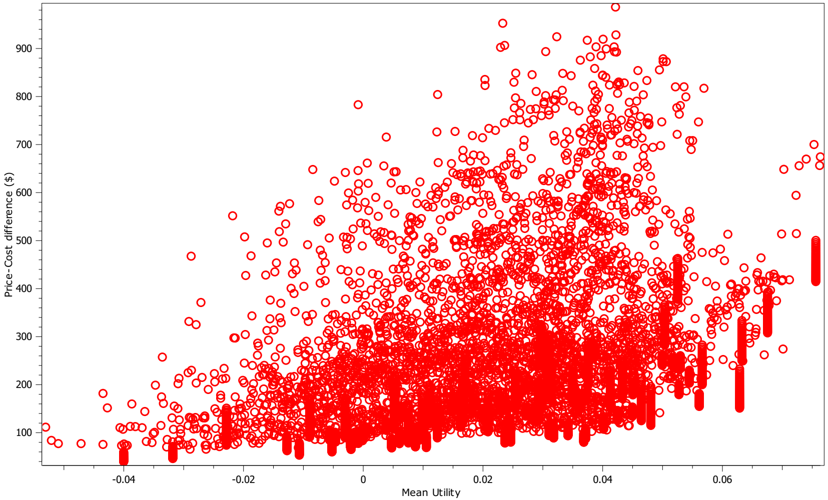
Average marginal cost by period and firm.



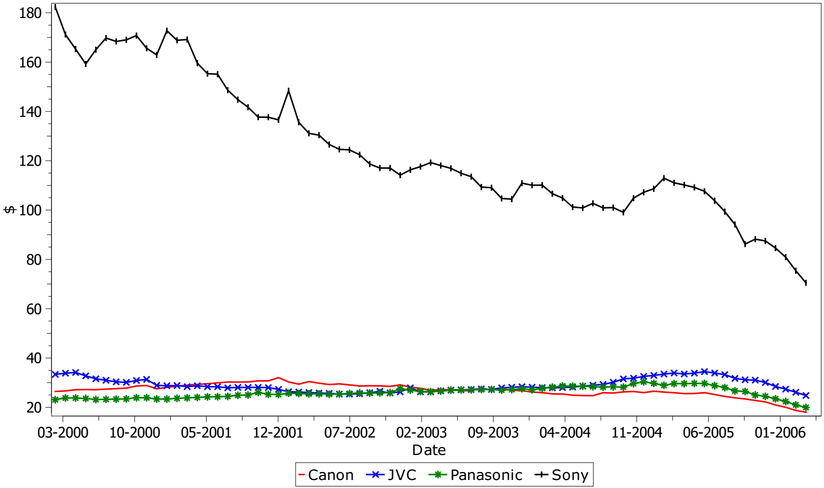
Average price-cost difference by period and firm.



Price-cost difference by flow utility.



Average difference between static and dynamic marginal costs.



- We estimate a model of technology adoption and diffusion in the context of network effects.
- We study the adoption of DVD players and its relationship to DVD titles.
- We provide solutions for a number of econometric issues that have not been well-addressed before.

Previous empirical research

- Successful network effects papers are cross-sectional (Rysman, 2004 and Ackerberg & Gowrisankaran, 2006).
- But canonical network effects problem is about dynamic diffusion.
  - fax machines, VCRs, CD players, computers, video games.

Previous empirical research

- Successful network effects papers are cross-sectional (Rysman, 2004 and Ackerberg & Gowrisankaran, 2006).
- But canonical network effects problem is about dynamic diffusion.
  - fax machines, VCRs, CD players, computers, video games.
- Typically use:
  - static models of demand.
  - a single measure of the complementary good, or installed base.
  - questionable instruments.
- Closest paper to our is Lee (2013).

Our Approach

- We estimate our structural model with time dummies.
- In a second stage, we estimate the relationship between time dummies and network variable.
    - Time series regression!
- We experiment with many network variables, and settle on number of new titles from recent movies.

Data

- March 1997 to October 2006.
- Monthly data on price and sales of DVD players by model.
- From NPD, (from retailers).
- Product characteristics.

Data

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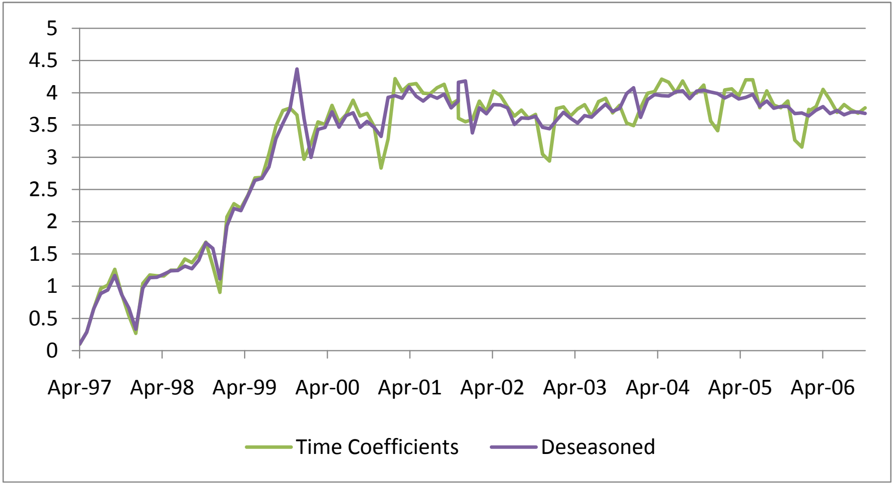
- Monthly data on price and sales of DVD players by model.
- From NPD, (from retailers).
- Product characteristics.
- Monthly data on DVD and movies (releases, revenue).
- Household survey data on holdings.

Time dummy coefficients



Structural VAR

- Model:

$$
\begin{aligned}
\theta_t &= \beta_0 + \beta_1 \theta_{t-1} + \beta_2 N_t + \beta_3 t + u_t. \\
N_t &= \gamma_0 + \gamma_1 N_{t-1} + \gamma_2 \theta_t + \gamma_3 t + \gamma_4 z_t + v_t.
\end{aligned}
$$

  - z is movie variable.

Structural VAR

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  - z is movie variable.
- Concern 1: Unit root in u_t?
- Concern 2: Auto-correlation in u_t?

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  - z is movie variable.
- Concern 1: Unit root in u_t?
- Concern 2: Auto-correlation in u_t?
- Concern 3: Simultaneity in y_t and x_t can be solved with z_t.

Second Stage Results: VAR

No Instrumenting

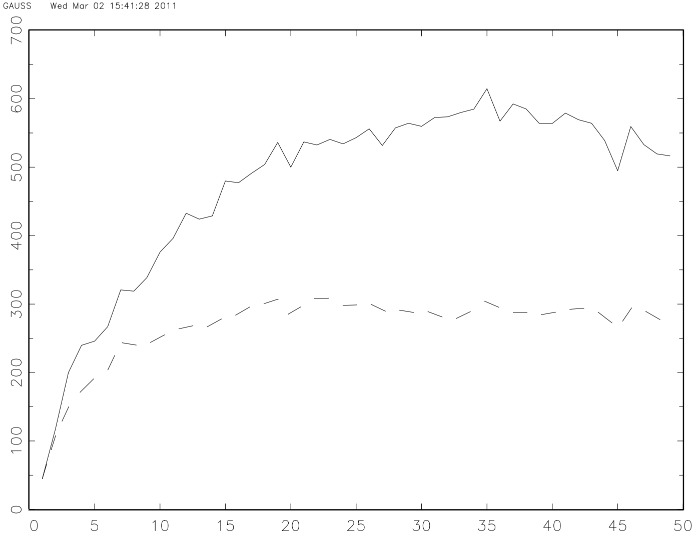
Constant	0.140	-0.077	-0.016
	(0.077)	(0.097)	(0.105)
Lag Y	0.913 *	0.782 *	0.742 *
	(0.031)	(0.049)	(0.086)
New DVD movie titles	0.010	0.035 *	0.032 *
	(0.005)	(0.009)	(0.011)
time	-0.001	0.010 *	0.006
	(0.001)	(0.004)	(0.007)
New titles X time		-0.0004 *	
		(0.00011)	
Cut-off date	none	none	Oct-01
Observations	114	114	54

Second Stage Results: VAR

Instrumental Variables

	New DVD Movie Titles	Time Coefficients
Constant	-3.435	-0.506
	(5.021)	(0.349)
Lag Time Coefficients	1.516	0.600 *
	(0.968)	(0.143)
New DVD movie titles		0.109 *
		(0.054)
time	0.478	-0.013
	(0.169)	(0.016)
New Movies (5 months ago)	0.380	
	(0.200)	
New Movies X Time	-0.009 *	
	(0.005)	
Cut-off date	Oct-01	Oct-01
Observations	54	54

Coefficients with and without Network Effect



Conclusion

- Dynamics are important in durable goods environments, such as new consumer electronics.
- Accounting for dynamics has important implications, both computationally and for results.
- We explore implications for supply side and for network effects estimation.

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