Dynamics of Consumer Demand for New Durable Goods

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Introduction

If you don't need a new set, don't rush to buy one. Prices will no doubt continue to drop over time, [and] you'll have more sets to choose from.
-ConsumerReports.org on 3D HDTVs

- Purchasing consumer electronics is a dynamic decision
- Prices for new consumer durable goods often decline rapidly during the first few years
- For digital camcorders: average price $930 in 2000, $380 by 2006
- Features, e.g. night shot and size, also improved dramatically
- This pattern is common across new consumer durable goods industries

Why do dynamics matter?

- A dynamic model is necessary to capture fact that consumers choose what to buy *and* when to buy
- Rapidly evolving nature of industry suggests importance of modeling dynamics
- Rational consumer in 2000 would likely have expected price to drop and quality to rise

Idea of study

- This paper specifies and estimates a structural dynamic model of consumer preferences for new durable goods
- We estimate the model using data on digital camcorders
- We use the model to:
  1. understand the importance of dynamics in consumer preferences
  2. evaluate dynamic price elasticities
  3. calculate a cost-of-living-index (COLI) for camcorders
- Methods of inference are also potentially applicable to other industries and questions

Why estimate COLIs for new goods industries?

- Concept is *compensating variations*
- Necessary for government transfer programs and to understand contribution of innovation to the economy
- Well-known “new goods” problem (Pakes, 2003)
- There is also the “new buyer” problem (Aizcorbe, 2005)
- More generally
  - Consumers may wait to buy a digital camcorder until prices drop or features improve
  - But, *high value* consumers will buy early and then be out of the market until features improve
  - The two effects work in opposite directions
- Suggests that estimation of a dynamic model is necessary to sort out different effects

Features of model

- Our model allows for product differentiation, persistent consumer heterogeneity and repeat purchases over time
- Berry, Levinsohn & Pakes (1995) [BLP] have shown the importance of incorporating consumer heterogeneity
- Much of our model is essentially the same as BLP
  1. Consumers make a discrete choice over available models
  2. Multinomial logit utility with unobserved characteristic and random coefficients
  3. Designed for model-level data but can also use consumer-level data when available
  4. Allows for endogeneity of prices
  5. Evolution of models not chosen endogenously, e.g. with respect to unobserved characteristics

Dynamics of our model

- Our model departs from BLP in the dynamics
  - Goods are durable and prices may fall
- We adapt Rust (1987) insight: consumers make rational, dynamic choice to keep or replace current product
  - Rust's model builds on vintage capital models by assuming a sunk cost of technology acquisition
- Consumers have rational expectations over future quality and price paths
- Consumers differentiated in willingness to pay and in relative disutility from price with persistence over time
  - These are the BLP insights adapted to a dynamic setting

Biases from not modeling dynamics

- Dynamics transforms consumption problem into an investment problem
- Firms will invest in capital if service flow is greater than rental cost:
  - Rental cost of capital is *difference* in present-value prices
  - For static models: increase in sales as prices drop
  - For dynamic models: increase only when drop ends
- Static estimation applied to durable goods purchase results in measurements error
  - Price coefficients biased towards zero
- Heterogeneous agents imply that population response to rising quality is smaller than average individual response
- May be hard to rationalize cross-sectional and dynamic substitution patterns with static model

Relation to literature

- Other recent papers have also been developing dynamic models of demand
  - Our paper builds on work by Melnikov (2012) among others
- Ours is the first paper to use BLP-style model of per-period demand and to allow for repeat purchases
- Several new papers use and extend our methods to examine related I.O. and antitrust questions
  - Shcherbakov (2009), Ho (2011) and Nosal (2012) estimate switching costs
  - Schiraldi (2011) examines dynamics of automobile market
  - Lee (2012) examines video-game platform competition
  - Zhao (2008) estimates digital camera market
- We provide code and assistance to implement our algorithm

Model

- Model starts at time $t = 0$ with introduction of new segment
- Unit of observation is a month
- Future discounted at rate β by consumers and firms
- Our model nests insights of Rust-style optimal stopping model inside BLP-style model
  - Our exposition first focuses on the single consumer
  - Ultimately, we model continuum of consumers
- Forward-looking consumer can purchase durable good, or hold outside good (with flow utility 0)
- Durable good does not depreciate, but consumer can only obtain utility from one good at a time

Consumer preferences

- At time t, the consumer chooses to purchase one of the J_t durable goods or to purchase no product

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- If she buys model j at time t she receives flow utility of:

  $$u_{jt} = f_{jt} - P_{jt} + \varepsilon_{jt}$$

  where
  - f_{jt} is model j's flow utility
  - P_{jt} is the disutility from price
  - ε_{jt} is an idiosyncratic error term, type 1 extreme value

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- If she doesn't buy, she receives flow utility of:
$$u_{0t} = f_{0t} + \varepsilon_{0t}$$
where
  - f_{0t} starts out at 0 (outside good)
  - $f_{0t} = f_{\hat{j}\hat{t}}$, if $t > \hat{t}$, $\hat{t}$ is most recent purchase time, and $\hat{j}$ is product purchased at $\hat{t}$

Consumer expectations

- At time t, consumer has $J_t + 1$ choices and maximizes expected discounted utility of future utility
- Consumer knows time all t information when making her decisions but does not know future $\vec{\varepsilon}$ shocks
- Future models vary due to entry, exit and price changes and the consumer may lack perfect information
- Let Ω_t denote number of models, model attributes and other factors that may influence future model attributes
- We assume that Ω_t evolves according to a Markov process, $P\left(\Omega_{t+1} | \Omega_t\right)$
- State space is $\left(\vec{\varepsilon}_t, f_{0t}, \Omega_t\right)$

Dynamics of consumer preferences

- Bellman equation prior to realization of $\vec{\varepsilon}$:

$$V(f_0, \Omega) = \int \max\{\overbrace{f_0 + \beta E\left[V\left(f_0, \Omega'\right) \middle| \Omega\right] + \varepsilon_0}^{\text{Value of keeping existing model}},$$
$$\max_{j=1,\ldots,J}\{\underbrace{f_j - P_j + \beta E\left[V\left(f_j, \Omega'\right) \middle| \Omega\right] + \varepsilon_j}_{\text{Value of upgrading to } j}\}\} g_{\vec{\varepsilon}}(\vec{\varepsilon})$$

  where "E" is expectation and " $'$ " is next period
- Interpretation:
  - First line: keep existing model, get f_0 going forward
  - Second line: upgrade, get f_j going forward
- Problem: dimension of Ω is huge

State space simplification

- Use aggregation properties of extreme value distribution to write:
  $$V\left(f_0, \Omega\right) = \ln\left[\exp\left(f_0 + \beta E\left[V\left(f_0, \Omega'\right) \middle| f_0, \Omega\right]\right) + \exp\left(\delta(\Omega)\right)\right]$$
  where *logit inclusive value* is:
  $$\delta(\Omega) = \ln\left(\sum_{j=1,\ldots,J} \exp\left(f_j - P_j + \beta E\left[\left. V\left(f_j, \Omega'\right) \right| \Omega\right]\right)\right)$$
- $\delta(\Omega)$ is the value of buying the preferred camcorder as opposed to holding outside good
  - See Anderson, De Palma and Thisse (1992); Rust (1987)
- The fact that utility from purchase depends only on δ suggests a simplifying assumption based on δ
- We focus on case where consumers only use δ (not Ω) to make predictions of δ'

Inclusive value sufficiency

- Let $g(\delta'|\delta)$ denote conditional density

Assumption: Inclusive Value Sufficiency (IVS)

If $\delta(\Omega) = \delta(\tilde{\Omega})$, then $g(\delta(\Omega')|\Omega) = g(\delta(\tilde{\Omega}')|\tilde{\Omega}')$ for all Ω, $\tilde{\Omega}$

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- Implies simpler state space and dynamic problem with:

$$\mathcal{V}\left(f_0, \delta\right) = \ln\left[\exp\left(f_0 + \beta E\left[\mathcal{V}\left(f_0, \delta'\right)|\delta\right]\right) + \exp\left(\delta\right)\right]$$

and:

$$\delta = \ln\left(\sum_{j=1,\ldots,J} \exp\left(f_j - P_j + \beta E\left[\mathcal{V}\left(f_j, \delta'\right)\middle|\,\delta\right]\right)\right)$$

- Dynamic problem defined by fixed point of:
  - (1) $\mathcal{V}$ (2) δ evolution (3) $g(\delta'|\delta)$

Expectations of δ evolution

- We assume rational expectations
- One option is perfect foresight
- We believe that limited ability to predict future model attributes is more realistic
  - For most specifications, we let perceptions about next period's δ be empirical density fitted to autoregressive specification:

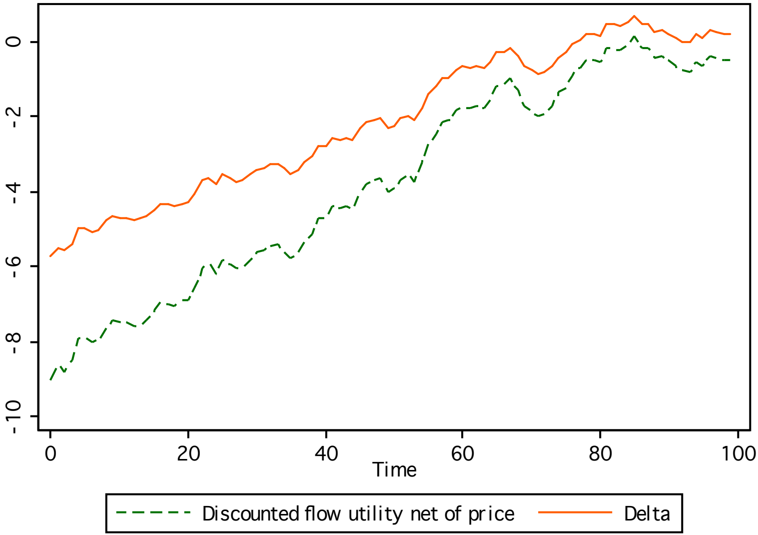
$$\delta_{t+1} = \gamma_1 + \gamma_2 \delta_t + \nu_{t+1}$$

- Similar – but not identical – assumptions as in Melnikov (2001) and Hendel and Nevo (2006)
  - Due to repeat purchases, we first need to define δ as entire future utility stream, not flow utility

Role of δ and IVS assumption in numerical example

- We consider example with one model each period:
  - Price is constant and quality f evolves with AR(1) process
  - Asymptote of discounted flow utility net of price: $f/(1-\beta) - P = 0.05$
- We first show the evolution of δ and $f/(1-\beta) - P$, with consumer knowing true evolution

Role of δ and IVS assumption in numerical example



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  - They approach each other over time as option value of waiting diminishes
  - Note also how our stationary model shows gradual asymptote to steady state

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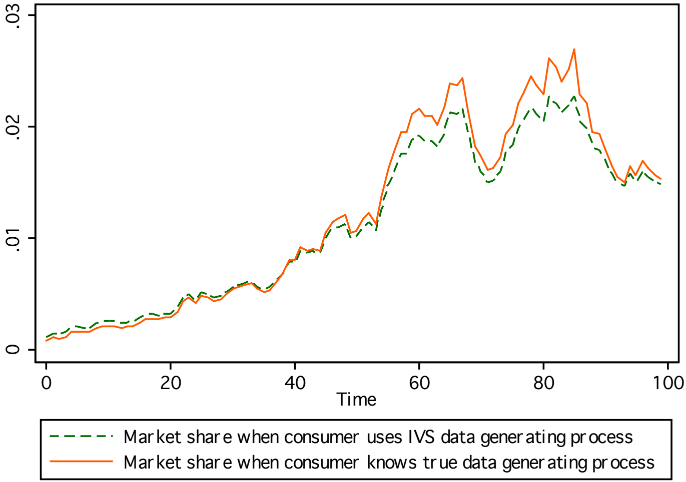

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- We next examine consumer who optimizes assuming that δ evolves with an AR(1), jointly solving $\mathcal{V}$, the δ evolution and the $g(\delta'|\delta)$ regression
  - Errors from approximation are small

Empirical tests of IVS assumption

We also try:

- adding J as a state
- Adding month effects
- Empirically testing the assumption

Aggregation and equilibrium

- Continuum of continuous consumers indexed by i
- Consumers differ in mean flow utility, price disutility, idiosyncratic shocks, and future expectations
  - Index terms by i: f_{ijt}, P_{ijt}, ε_{ijt}, δ_{it}, $\mathcal{V}_i$ and $(\gamma_{1i}, \gamma_{2i}, \nu_{it})$
- We let flow utility be: $f_{ijt} = x_{jt}\alpha_i^x + \xi_{jt}$
- We let price disutility be: $P_{ijt} = \alpha_i^p \ln(p_{jt})$
- α_i^x, α_i^p are (time invariant) consumer random coefficients
  - We assume normal distribution
  - We estimate parameters for mean (α^x, α^p) and variance (Σ)
- Underlying supply model
  - Products arrive according to stochastic process
  - After observing model characteristics and demand shocks, firms simultaneously make pricing decisions

Inference

- Parameters are α, Σ and β
  - Difficult to estimate discount factor, so we set $\beta = .99$ at level of month
- Following BLP, we specify a GMM criterion function:

$$G(\alpha, \Sigma) = z'\vec{\xi}(\alpha, \Sigma)$$

- Actual criterion function also includes micro-moments as in Petrin (2002)
- We estimate parameters to satisfy:

$$\left(\hat{\alpha}, \hat{\Sigma}\right) = \arg\min_{\alpha,\Sigma} \left\{ G(\alpha, \Sigma)' \, W G(\alpha, \Sigma) \right\}$$

Inference: continued

- To solve for $G(\alpha, \Sigma)$ we need to solve for market shares for any i, which involves:
  1. Solving for consumer decision problem by solving joint fixed point
  2. Starting with assumption that consumers hold outside good at time 0
  3. Calculating conditional probability of purchase based on holdings and δ as:

$$\frac{\exp(\delta_{it})}{\exp\left(\mathcal{V}_i(f_{i0t}, \delta_{it})\right)} \times \frac{\exp\left(f_{ijt} - P_{ijt} + \beta E\left[\mathcal{V}_i\left(f_{ijt}, \delta_{i,t+1}\right) \mid f_{ijt}, \delta_{it}\right]\right)}{\exp(\delta_{it})}$$

  4. Updating shares and holdings each period
- We then integrate across consumers i using simulation, as in BLP

Obtaining ξ from shares

- Define *mean flow utility* as:

$$F_{jt} = x_{jt}\alpha^x + \xi_{jt}, j = 1, \quad \dots, J_t$$

- Moment condition requires backing out $\vec{\xi}$ from observed shares:

$$s_{jt} - \hat{s}_{jt}\left(\vec{F}, \alpha^p, \Sigma\right)$$

- We use:

$$F_{jt}^{new} = F_{jt}^{new} + \psi \cdot \left(\ln(s_{jt}) - \ln\left(\hat{s}_{jt}\left(\vec{F}^{old}, \alpha^p, \Sigma\right)\right)\right), \forall j, t$$

- We solve for simultaneous fixed point of F_{jt}, $\mathcal{V}_i$ and δ_i, updating $g(\delta_i'|\delta_i)$ and conditional probability of purchase
- At fixed point, true shares equal predicted shares and consumers are optimizing

Why is our method useful?

- Alternative might be maximum likelihood
- Maximum likelihood that accounted for endogeneity would have to explicitly calculate dynamic firm problem
- Inversion method allows us to estimate consumer model without explicitly solving equilibrium
- Computationally much easier and needs (somewhat) less assumptions

Instruments

- We use all model characteristics as instruments
- Use also mean model characteristics within a firm at time t and overall at time t
- Use also count of number of models within a firm and overall at time t

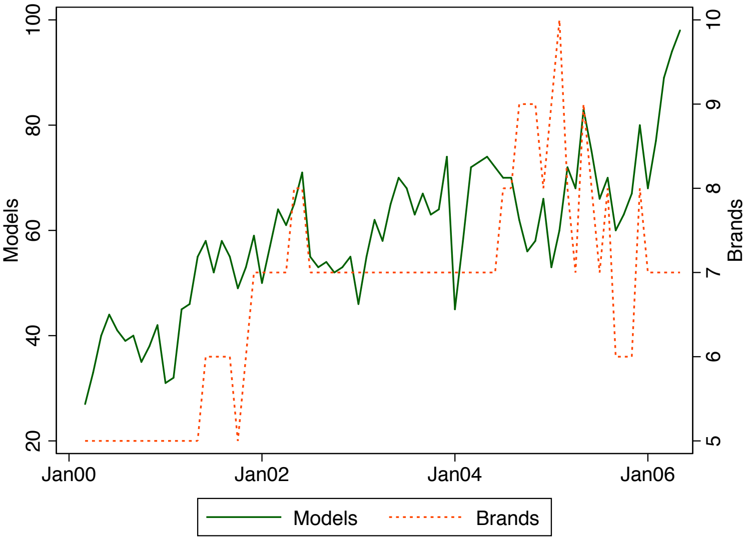
Identification

- Our parameters all static consumer preference parameters
- This is true even for the repeat purchase model because of reasonably strong assumptions: digital camcorders don't wear out; there is no resale market for them; and only one digital camcorder per household is useful
- Identification arguments similar to static discrete choice literature, e.g. Berry (1994), Petrin (2002)
- Variation in "nearby" models will identify price elasticities
- Random coefficients identified by variation in choice sets; e.g. how do consumers substitute as choice set varies
- Dynamics *helps* identification: random coefficients also identified by endogenous differences in tastes over time and substitution *across* time

Data

- **Aggregate data on prices, quantities and characteristics for digital camcorders**
- Prices declining and quantities rising over time
- Big issue is Christmas; we seasonally adjust data to account for Christmas
- Data from 2000 to 2006; features improving over time
- Some specifications use household penetration data from ICR-CENTRIS

Data



Models
Brands
100
80
60
40
20
10
9
8
7
6
5
Jan00
Jan02
Jan04
Jan06
Models
Brands

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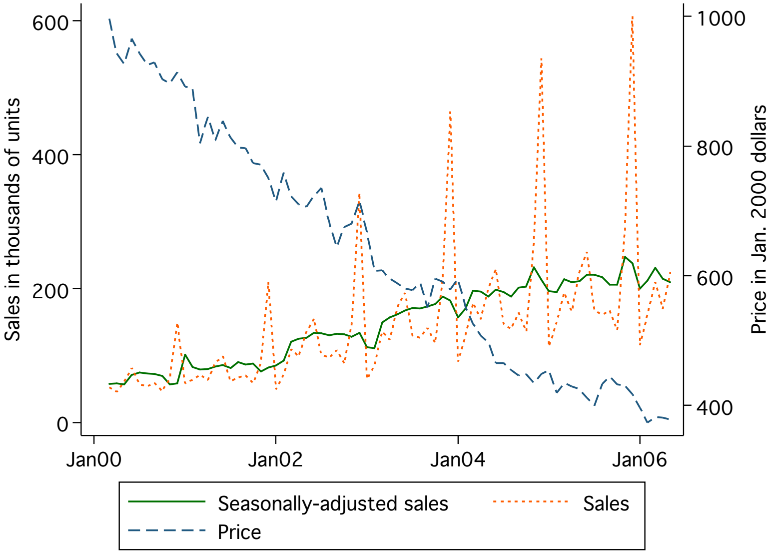

Sales in thousands of units
600
400
200
0
Price in Jan. 2000 dollars
1000
800
600
400
Jan00
Jan02
Jan04
Jan06
Seasonally-adjusted sales
Sales
Price

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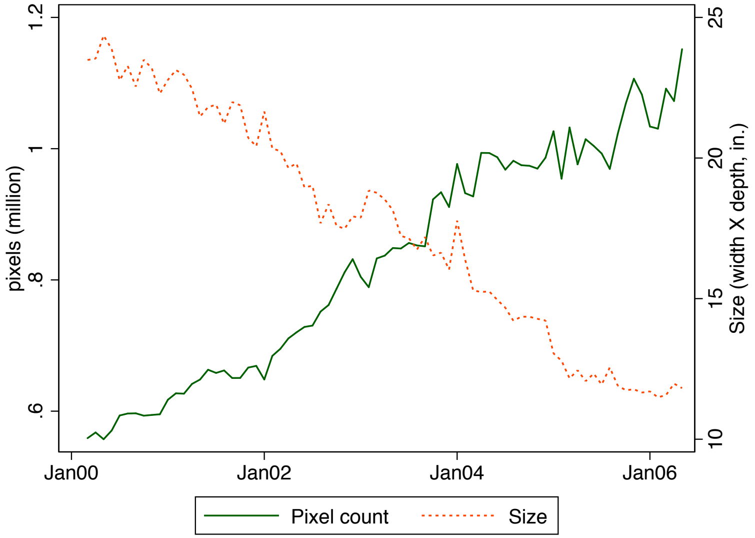
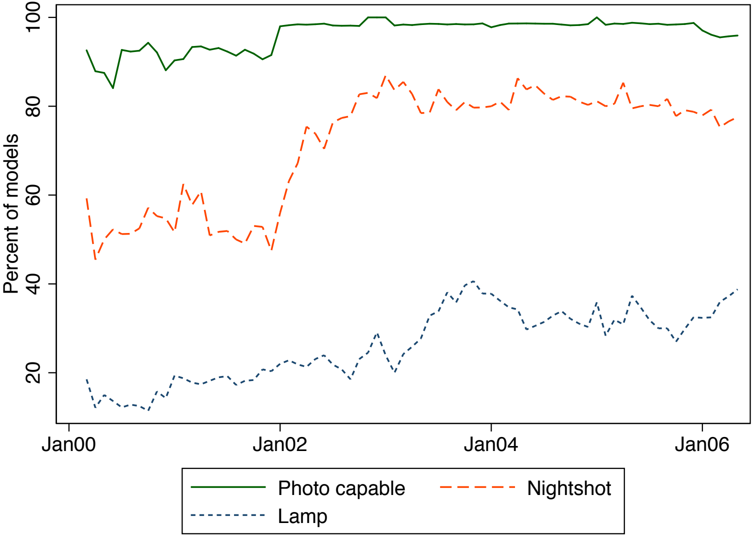


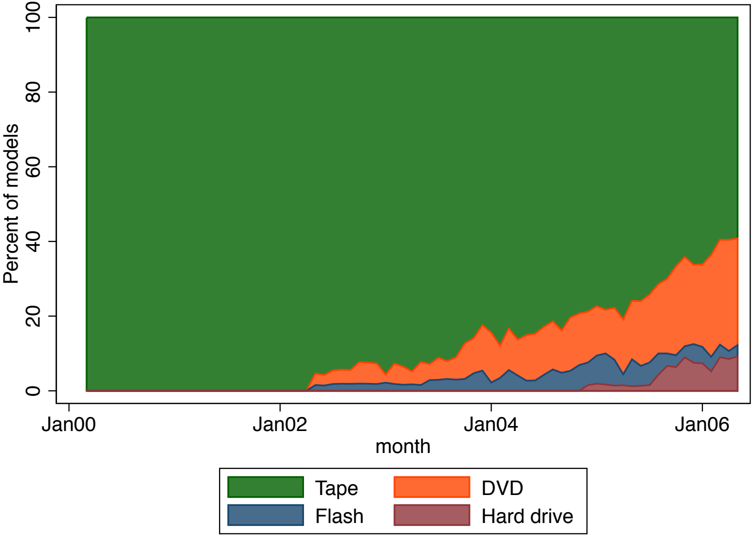
pixels (million)
1.2
1
.8
.6
Size (width X depth, in.)
25
20
15
10
Jan00
Jan02
Jan04
Jan06
Pixel count
Size

Data



Percent of models
100
80
60
40
20
Jan00
Jan02
Jan04
Jan06
Photo capable
Nightshot
Lamp

Data



Percent of models
100
80
60
40
20
0
Jan00
Jan02
Jan04
Jan06
month
Tape
DVD
Flash
Hard drive

Data

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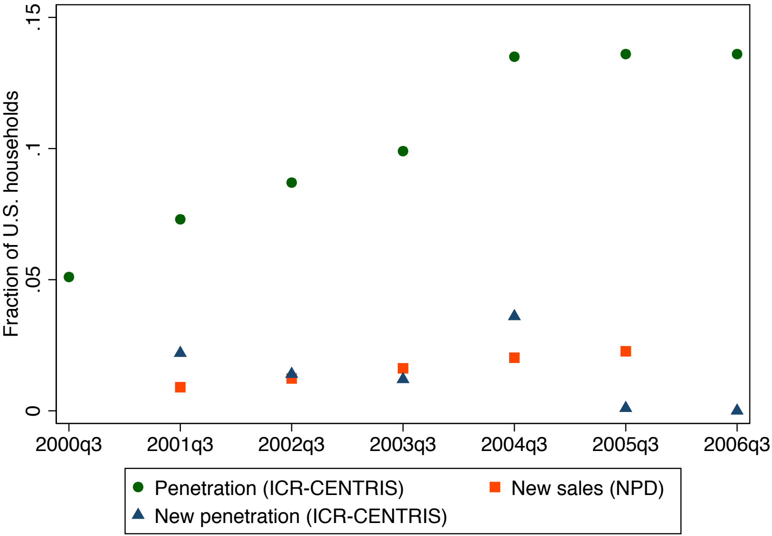

Fraction of U.S. households
0
.05
.1
.15
2000q3
2001q3
2002q3
2003q3
2004q3
2005q3
2006q3
Penetration (ICR-CENTRIS)
New sales (NPD)
New penetration (ICR-CENTRIS)

Results and fit of the model

Parameter estimates

- **Estimates from static model and dynamic model with and without repeat purchases and micro moments**
- **Non-nested tests reject both static and non-repeat purchase dynamic model in favor of dynamic model**
- Robustness specifications

Fit of the model

- Average unobserved characteristic ξ_{jt}
- Evolution of δ_{it}
- Difference between δ_{it+1} and its period t prediction
- Fail to reject null of no serial correlation in ν_t
- Evolution of repeat purchase sales

Results and fit of the model

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.

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Results and fit of the model

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

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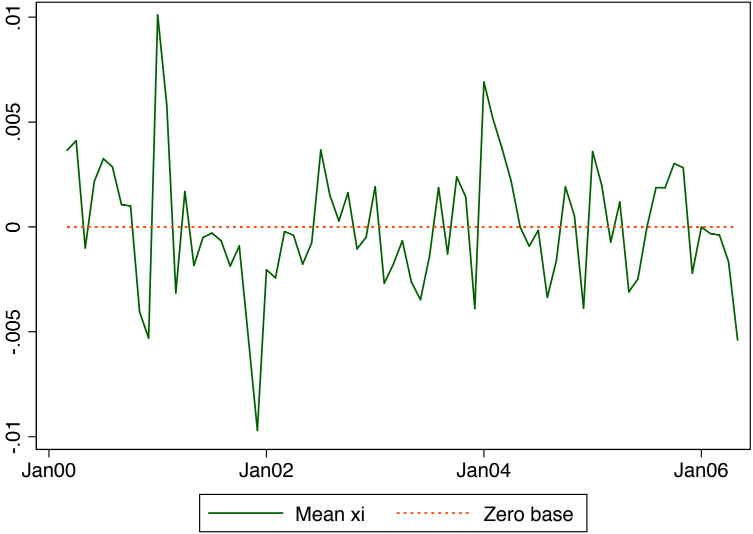

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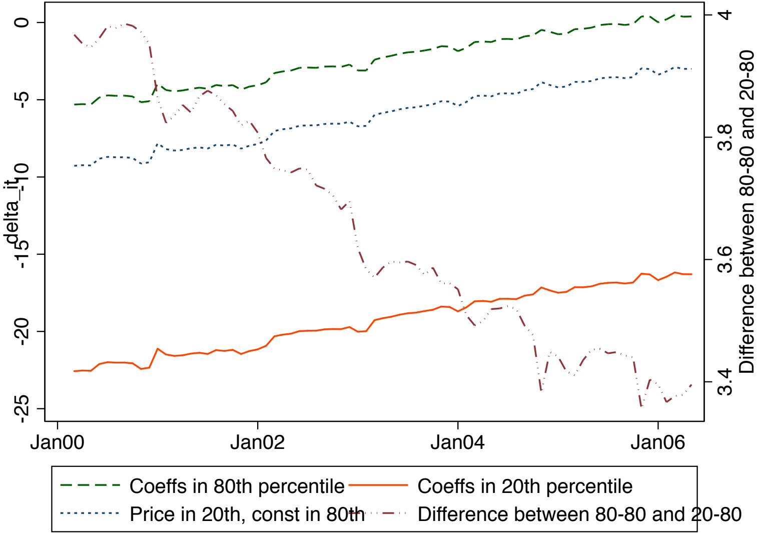

Results and fit of the model

Parameter estimates

- Estimates from static model and dynamic model with and without repeat purchases and micro moments
- Non-nested tests reject both static and non-repeat purchase dynamic model in favor of dynamic model
- Robustness specifications

Fit of the model

- Average unobserved characteristic ξ_{jt}
- Evolution of δ_{it}
- **Difference between δ_{it+1} and its period t prediction**
- **Fail to reject null of no serial correlation in ν_t**
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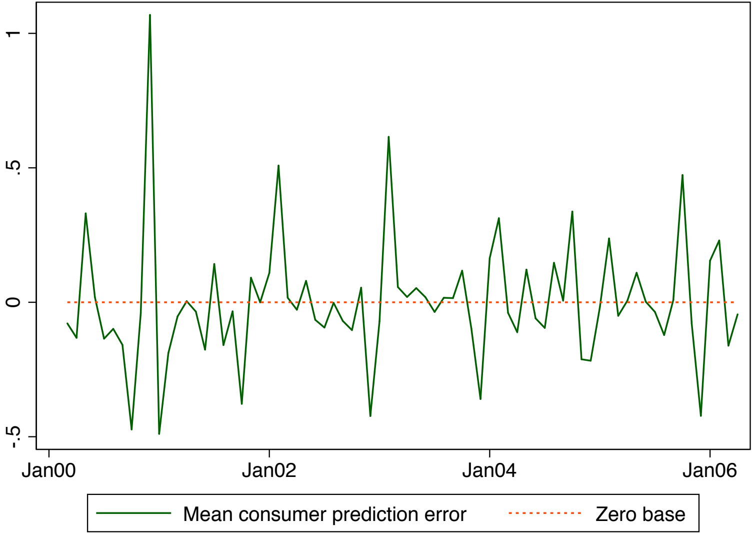

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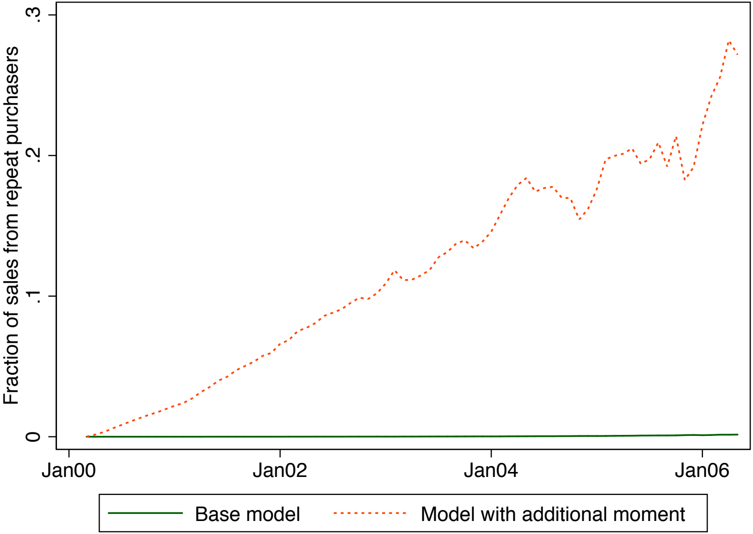

Implications of the results

- **Evolution of camcorder sales under different expectation assumptions for dynamic model**
- **Static elasticities are virtually zero**
- Industry dynamic price elasticities
- Dynamic price elasticities for Sony DCRTRV250

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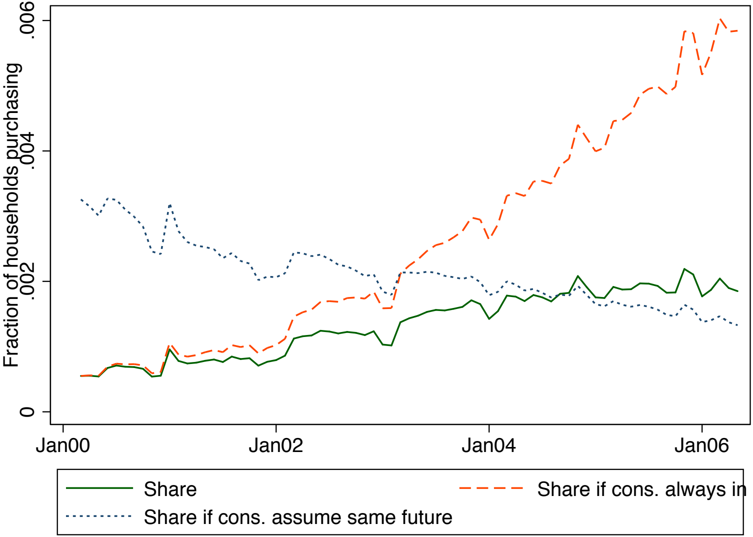

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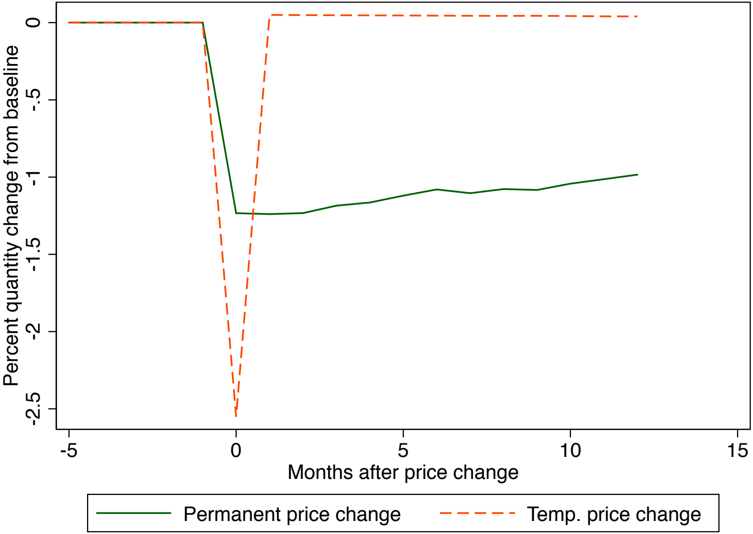

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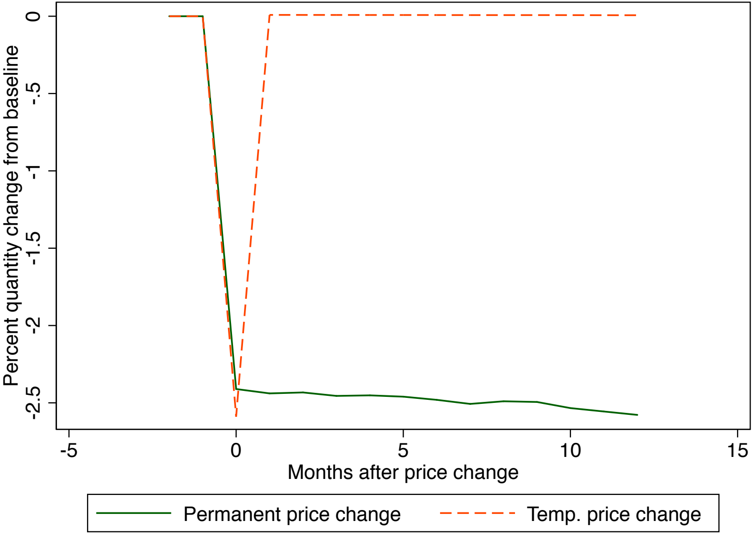


Application: Cost-of-living Indices

Some differences between implications of our model and the standard approach:

- New Buyer problem: Heterogeneity of consumers across periods
- New Goods problem: How to handle goods that enter and exit
- Expectations 1: A surprising price drop raises welfare more than an expected one.
- Expectations 2: A surprising price drop helps everyone, even non-buyers.
- Expectations 3: Future COLI changes affect welfare today.
- Quantities: Importance of price changes increases as sales do.

Our approach

- Imagine the set of state-contingent taxes that keep average expected welfare constant
- Equivalently, the set of state-contingent taxes that keeps average flow utility constant
  - Assume that consumers dynamically optimize
  - Means we don't have to average over all possible sequences of outcomes to compute price index
- Compute tax for sequence of realized states
- Assume price is paid in an infinite stream of constant payments

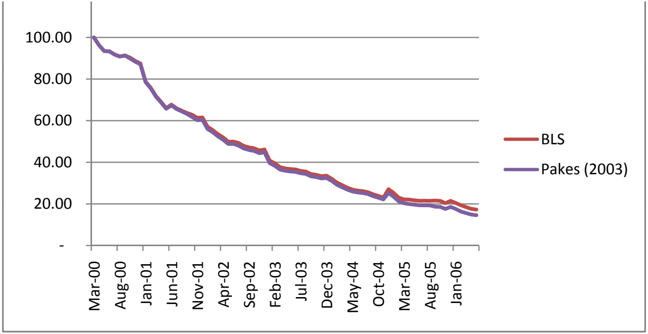
Our implementation of the BLS approach

- Laspeyres price index:

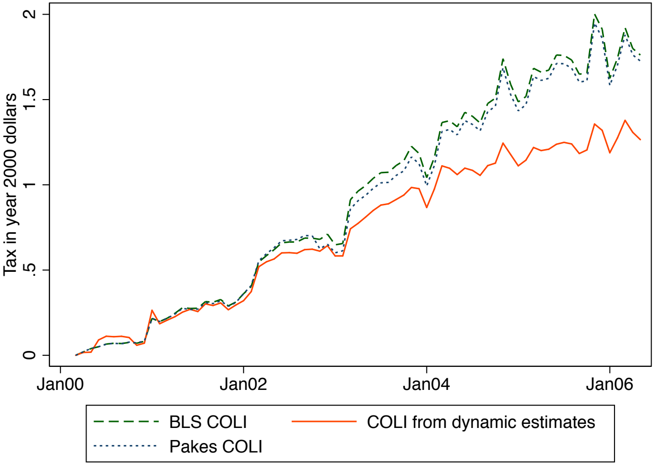
$$\frac{I_{t+1}}{I_t} = \frac{\sum_{j=1}^{J_t} s_{jt} p_{j,t+1}}{\sum_{j=1}^{J_t} s_{jt} p_{jt}}$$

- Need assumptions on prices for models that exit
  - BLS: impute price from average price drop
  - Pakes (2003): predict price from a regression on characteristics
- Good 0 is outside option and has a price that doesn't change
- Multiply price index by average price at $t = 0$ ($969) to get equivalent to our tax

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
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- 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
- These diverge because as households 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

- Dynamic model of consumer preferences with repeat purchases and random coefficients gives more sensible results
- Methods that we developed here useful for estimating dynamic demand for durable goods for other industries and answering other questions
- Dynamic estimation of consumer preferences is both feasible and important for new goods industries
- New buyer problem is important in determining COLIs for camcorders
- Long-run industry elasticity substantially smaller than short-run industry elasticity
- Future avenue of research is to analyze firm side