Dynamics of Consumer Demand for New Durable Goods

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Introduction: Motivation

- In many durable goods setting, the choice of when to buy is as important as what to buy
- This is specially true for consumer electronics, since prices are expected to fall during the its lifetime

Introduction: Objective

Objective:

- Specify a structural dynamic model of consumer preferences for new durable goods,
- Estimate the model using data on digital recorders,
- Use model to evaluate elasticities and cost-of-living indices for this market.

Introduction: The Market

- About 11 million units of camcorders were sold in the U.S. from 2000 to 2006,
- During this time the average price dropped from $930 to $380,
- Meanwhile, the average pixel count rose from 580k to 1.08m,
- The number of models grew from less than 30 to almost 100,
- and the average sales grew by a factor of 2.6.

Model

- The industry starts at time $t = 0$,
- The consumer has infinite horizon and discounts the future at rate β
- The consumer can benefit from at most one camcorder in a period,
- There is no resale market, if the consumer choose to change his camcorder, the old one is discarded costlessly.

Model

The utility of each camcorder j at time t is:

$$u_{jt} = f_{jt} - P_{jt} + \varepsilon_{jt}, \text{ for } j = 1, \ldots J_t$$

Where:

- f_{jt} is the net flow utility of camcorder j at time t,
- P_{jt} is the disutility of price of camcorder j at time t,
- ε_{jt} is the idiosyncratic type 1 extreme value term, distributed *i.i.d.* across models and time periods.

Model

- A consumer who does not purchase any model at time t receives $u_{0t} = f_{0t} + \varepsilon_{0t}$,
- Where f_{0t} is the flow utility of the good that the consumer possess at time t,
- If the consumer possess the outside good then $f_{0t} = 0$.
- Finally the consumer chooses j that has the maximum utility.

Model

Therefore, the consumer value function can be written as:

$$V(f_0, \Omega) = \int \max \Big\{ f_0 + \beta \, \mathbb{E}[V(f_0, \Omega')|\Omega] + \varepsilon_0, \tag{1}$$

$$\max_{j=1,\ldots,J} \{ f_j - P_j + \beta \, \mathbb{E}[V(f_j, \Omega')|\Omega] + \varepsilon_j \} \Big\} g_{\vec{\varepsilon}}(\vec{\varepsilon}) d\vec{\varepsilon} \tag{2}$$

Where:

- $\vec{\varepsilon} \equiv (\varepsilon_0, \ldots, \varepsilon_{J_t t})$
- Primes (e.g. Ω') denotes the next period value of a variable.
- The state evolves according to some Markov process: $g_\Omega = (\Omega_{t+1}|\Omega_t)$.

Model

- Ω_t denote the current industry state and includes: The number of models J_t, the price disutility and mean flow utility for each model, and any other factor that influence future model attributes,
- Ω has a very large dimension resulting in a curse of dimensionality,

- In order to get around this we proceed by using the aggregation properties of the extreme value distribution to express the previous equation as:

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

Where $\delta(\Omega)$ is defined as:

$$\delta(\Omega) = \ln\left(\sum_{j=1,\ldots,J} \exp(f_j - P_j + \beta + \mathbb{E}[V(f_0, \Omega')|\Omega])\right)$$

Model

We further simplify the process by assuming:

Assumption

Inclusive Value Sufficiency (IVS):
If $\delta(\Omega) = \delta(\tilde{\Omega})$, then $g_\delta(\delta(\Omega')|\Omega) = g_\delta(\delta(\tilde{\Omega}')|\tilde{\Omega})$ for all $\Omega, \tilde{\Omega}$.

- The IVS assumption imply that all states with the same $\delta(\Omega)$ have the same expected value,
- Thus, it is sufficient for the consumer to track only two scalar variables: f_0 and δ.

Model

Finally, we rewrite the problem as:

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

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

We also assume that the consumer has a limited ability to predict future model attributes, we say:

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

Where

- γ_1 and γ_2 are incidental parameters,
- ν_{t+1} is normally distributed with mean 0 and unobserved at time t.
- Note that this implies that if $0 < \gamma_2 < 1$

Aggregation

- Until now we have considered the decision of a single consumer to continue we have to define individuals characteristics and aggregate,
- Consumers differ in their mean flow utility, disutility of price, idiosyncratic shocks, logit inclusive values, Bellman Equation, and expectations processes for the future.
- That is, those terms are indexed by i: $f_{ijt}, P_{ijt}, \varepsilon_{ijt}, \delta_{ijt}, \mathcal{V}_{ijt}, \gamma_{1i}, \gamma_{2i}, \nu_{it}$.

Aggregation

Individual net flow utility for model j at time t is:

$$f_{it} = x_{jt}\alpha_i^x + \xi_{jt}$$

Where:

- x_{jt} is observed characteristics of camcorder,
- ξ_{jt} is unobserved characteristics, our error term,
- α_i^x are consumer i's coefficients on observed characteristics.

Price disutility is given by:

$$P_{ijt} = \alpha_i^p \ln(p_{jt})$$

Where α_i^p is the price coefficient and p_{jt} is price.

- We define $\alpha_i = (\alpha_i^x, \alpha_i^p)$ to simplify notation,
- and say that α_i **has mean** α **and variance** Σ.

Supply

- For the supply side, we assume that models arrive according to some exogenous process and that their characteristics evolve exogenously as well,
- After observing consumer endowments, x_{jt} and ξ_{jt} for all current models, firms simultaneously make pricing decisions in a Markov Perfect Equilibrium,
- Firms cannot commit to prices beyond the current period.

Inference

In order to make inference, we define the aggregation as follows:

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

- Note that: $f_{ijt} = F_{jt} + (\alpha_i^x - \alpha^x)x_{jt}$
- and $(\alpha_i^x - \alpha^x) \sim N(0, \Sigma)$

Beta is 0.99

$$\text{Beta} = 0.99$$

Inference

- Following BLP we have the following GMM criterion function:

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

And therefore our estimatives are defined by:

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

Inference

In order to calculate $\vec{\xi}(\alpha, \Sigma)$, we need to solve the market shares, which are given by the consumer maximization problem.
The *conditional probability of purchase* is defined as:

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

Inference

- We now match the predicted market share with the data, by doing to following interactive process:
- Start at $t = 0$ with $s_{00} = 1$. Everyone holds the outside good,
- Update conditional probability of purchase according to previous equation until fixed point,
- integrate of consumers to find market share.
- Choose $\vec{F}$ in order to match predicted values with data. That is:

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

Inference

We update $\vec{F}$, by the following process:

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

Where ψ is a tunning parameters set to $1 - \beta = 0.01$.

Inference

- Authors can't prove that these equations have a unique fix point,
- But different starting values were used and have always obtained convergence to the same solution.
- Therefore the following is being assumed:

Assumption

For any vector of parameters (α^p, Σ), there is a unique vector $\vec{F}$ such that $\vec{s} = \vec{\hat{s}}\left(\vec{F}, \alpha^p, \Sigma\right)$.

Identification

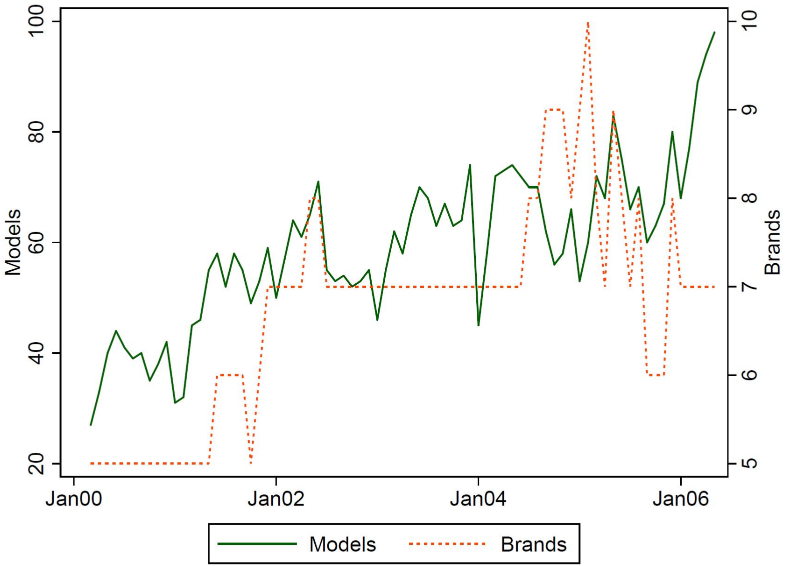
- The increase in market share of model j associated with a change in a characteristic of j identifies the mean of α,
- The models from which j draws markets shares identify Σ,
- In order to identity the extent of repeat purchasing, additional household survey data is used.

Data

- The primary data source in a panel of model-level data for digital camcorders, collect by NPD Techworld, which covers 80% of the market
- We observe 383 models and 11 brands, monthly, from March 2000 to May 2006,
- For each model at each month we observe price, number of units sold and other characteristics.
- Outliers, such as product with very low sales, very high or very low prices are excluded. Less then 3% of the date is excluded this way.

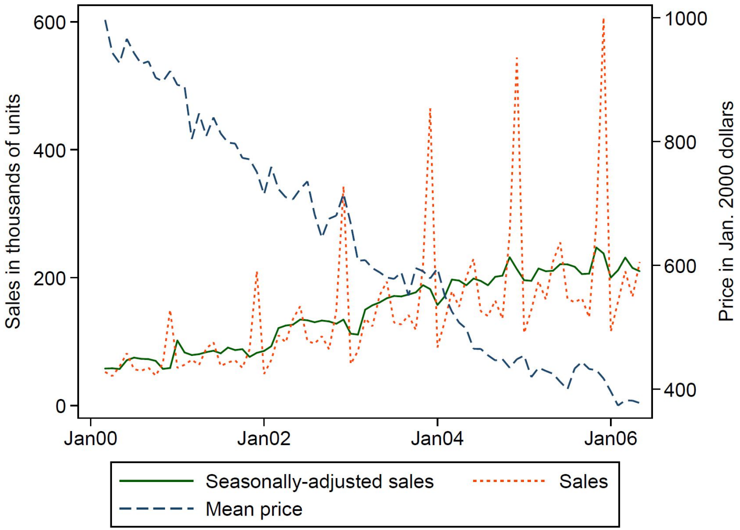
Data - Number of models increases

Figure 1: Number of brands and models over time



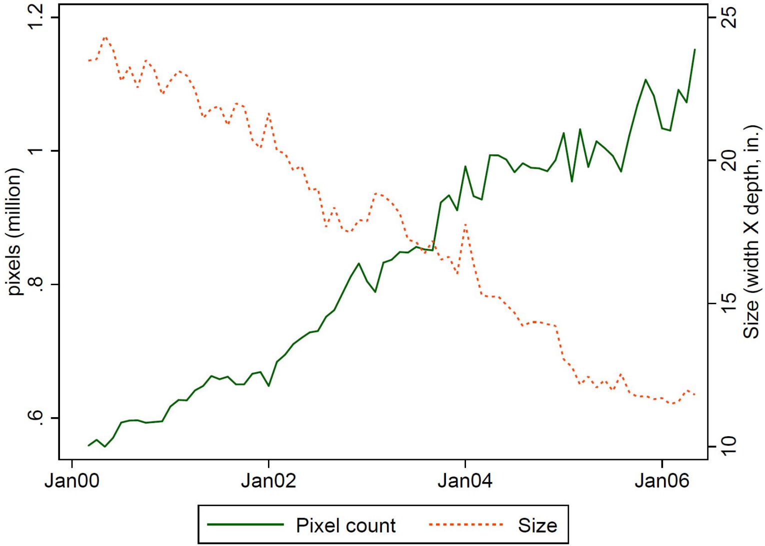
Data - Prices falls sales increases

Figure 2: Prices and sales for camcorders



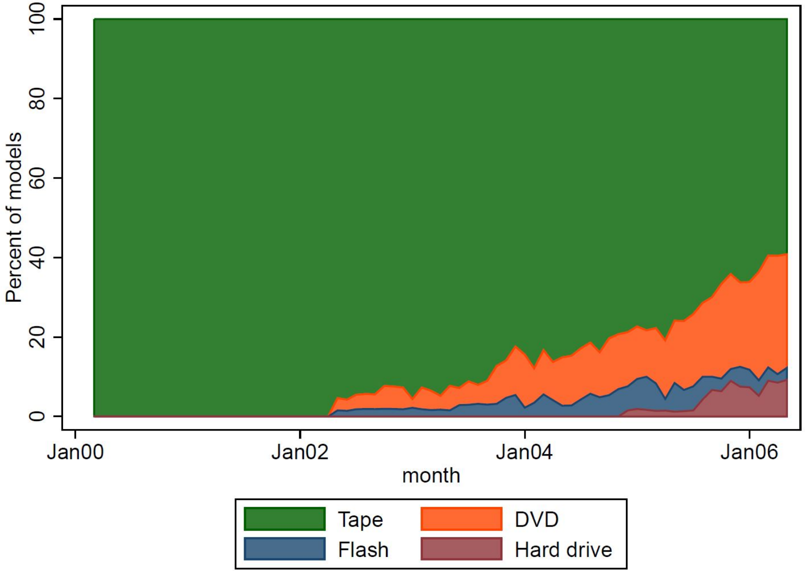
Data - Characteristics improve over time

Figure 3: Pixel count and camcorder size over time



Data - Media Type

Figure 5: Recording media over time

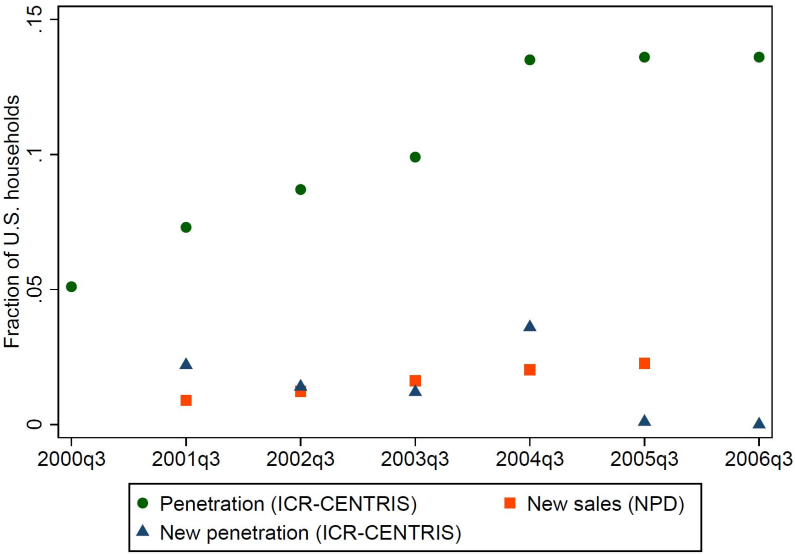


Data - ICR-CENTRIS

- Finally ICR-CENTRIS data is used to identify repeated purchase.
- Data shows rapid growth in penetration early on in the sample but no growth at the end,
- This is not entirely consistent with sales data. The penetration is larger than increase in sales at the beginning and way too low at the end,
- Nevertheless this suggest that repeated purchased is very important on the end of our sample.

Data - ICR-CENTRIS

Figure 6: Penetration and sales of digital camcorders



Results

Table 1: Parameter estimates

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)/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) *
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) *

Results

- Column 1 presents the results of or base model,
- Coefficients have the expected direction and are significant, that is, price decrease utility, quality measures increase utility.
- The low magnitude of quality coefficient are a consequence of the dynamic model and the coefficient are $(1-\beta)$ times smaller than they would be in static model.
- Parameters on characteristics are smaller in absolute value than the constant term. This imply that difference between camcorders are small relative to the outside good.

Results

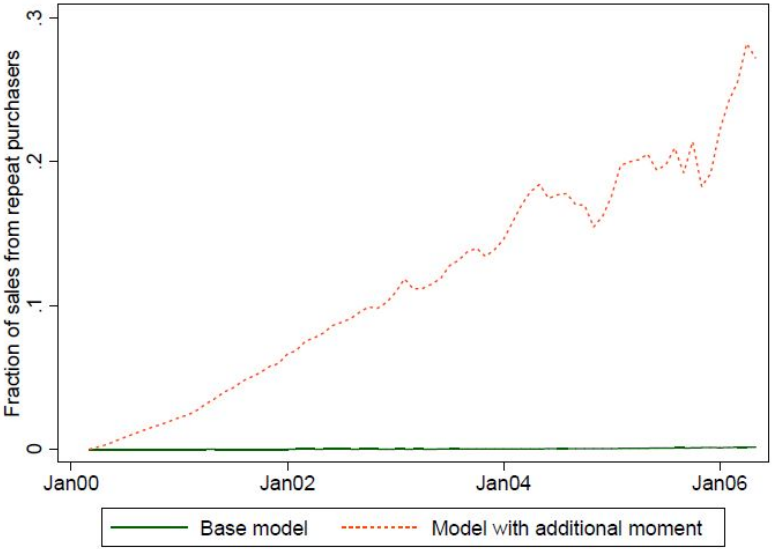
- Column 2 provides the same base model, but where individuals are restricted to purchase at most one digital camcorder ever,
- Column 2 coefficient are not reasonable.
- Column 3 shows the results in a static model, again coefficient are not reasonable, particularly price variance skyrocketed.

Results

- Even if Column 1 is significantly different from Column 2, repeating purchase represent only 0.25% of total purchase.
- This is not consistent with evidence.
- Column 4 tries to address by matching repeating purchase with penetration data.
- Coefficients of Column 4 is consistent with the results in the Base model

Results: Repeated purchase

Figure 8: Evolution of repeat purchase sales



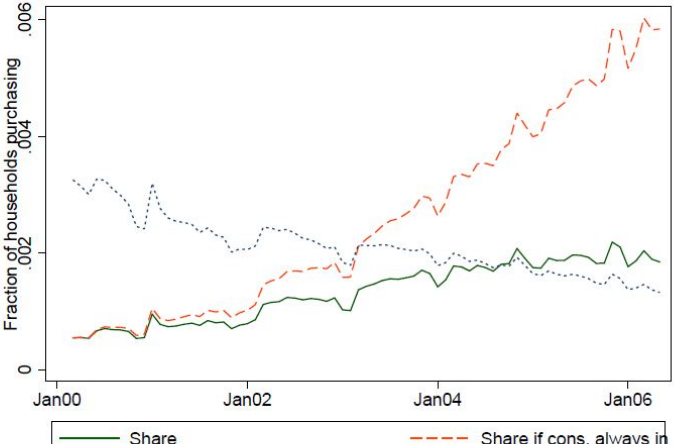
Results: Logit error assumption

- Logit error implies unrealistic welfare gain from new products,
- To test for it, we add $ln(J_t)$ as regressor. Finding a coefficient of 0 implies that logit model is well-specified, finding a coefficient of -1 implies that is no demand expansion effect from variety,
- We find a value of -0.013 which is significantly different from 0.
- But since "it is very close to zero" we conclude that the Logit Error assumption is reasonable.

Results: Comparitive analysis

- If price and quality are assumed not to change market share have radically different behaviour
- If camcorder were not a durable good, to the surprise of consumers, market share would rise even faster.

Figure 11: Evolution of digital camcorder sales under different assumptions

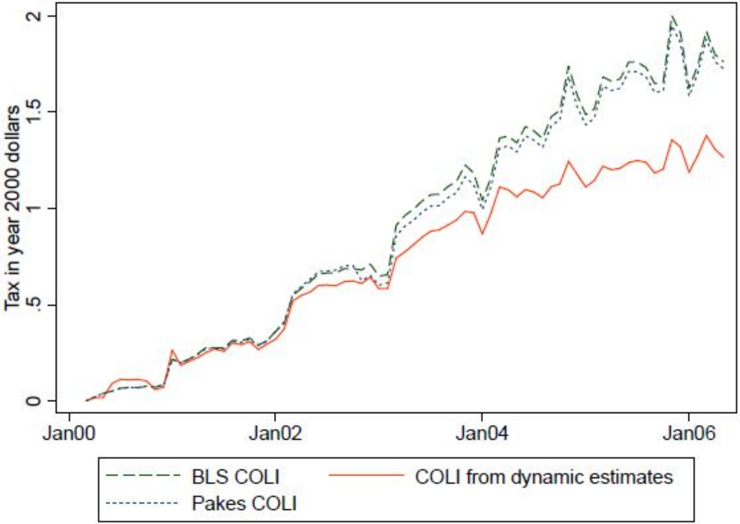


Results: COLI

- A new Cost of Living Index is derived from our dynamic model,
- This is done by measuring a compensating variation that makes the average expected value function to be constant over time,
- This new COLI substantially differ from standards CPIs measures,
- Which shows that the "news buyer problem", that is the fact the prices drop on durable goods disproportionally benefits consumers with lower evaluation, to be empirically important.

Results: COLI

Figure 14: Average monthly value from camcorder market



Conclusion

- The paper develop new methods to estimate dynamics of consumers preferences for new durable goods,
- The model can be used to measure welfare impact of new durable good,
- It's shown that initial market share for digital camcorders was not higher because of rational expectation of price and quality.
- Standard COLI's overstate the welfare gain of market evolution, because ignore the fact that later adopters tend to value product less than earlier adopters.

Extras

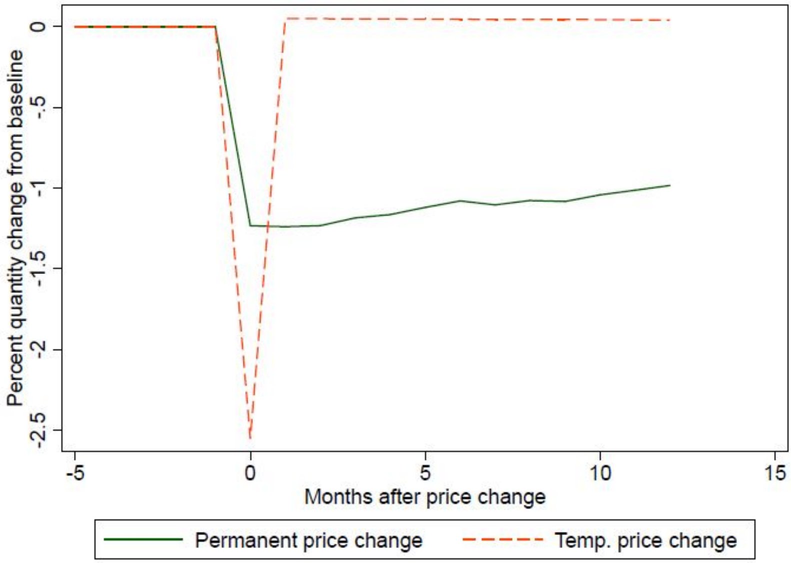
Table 2: Robustness

Parameter	State space includes number of products (1)	Perfect foresight (2)	Dynamic model with extra random coefficients (3)	Linear price (4)	Melnikov's model (5)	Month dummies (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)/10	.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.

Extras

Figure 12: Industry dynamic price elasticities



Extras

Figure 13: Dynamic price elasticities for Sony DCRTRV250

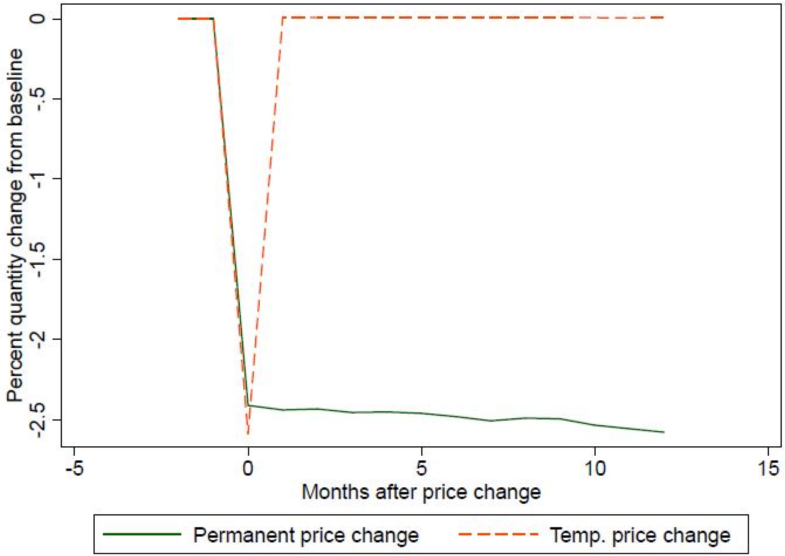


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Figure 9: Evolution of δ_{it} over time