An Experimental Component Index for the CPI: From Annual Computer Data to Monthly Data on Other Goods.

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Background

- Until recently, the component indices used to construct the CPI were matched model indices (explain).
- Earlier paper (Pakes, 2003) explains that this generates a selection bias caused by the exit of goods. Goods that exit, and hence whose price changes are not included in the index, are disproportionately goods whose characteristics have been obsoleted, and hence whose prices have declined.
- Then shows that if utility is defined on a characteristic space, there are gradient con-

ditions which insure that hedonic regressions can be used to bound the compensating variation needed to compensate consumers for changes in the choice set (the Konus-Laspeyres argument in characteristic space). In this paper we simply assume those conditions are satisfied.

- The bound is not tight because it does not account for; (i) the inframarginal rents to consumers who would have purchased the good at the highest observed price, and (ii) it does not account for substitution possibilities (geomean index has been introduced to "account" for the latter).

- Note the hedonic is *not* used for a prediction of what the price of the good would be were it not to have exited. It is a "reduced form" summary of the data on what a consumer would have to pay in order to get a good with similar characteristics to those of the good that exited.

- That summary bears no necessary relationship to demand or cost primitives, as a result it must
  - **be updated every period**,
  - have no cross-period constraints, and
  - include all relevant characteristics.

  Subject to these requirements, any sufficiently rich functional form can be used.

- When applied to computers the hedonic was much lower than the matched model index (-16.4% to +2.8%).

- Until very recently hedonic predictions that were based on regression functions that were updated every period could not be done within the BLS's monthly time constraints.

- BLS's data gatherers now record the data they gather on hand held computers whose contents are downloaded nightly onto a central BLS data management system. This has changed the possiblities for doing hedonic regressions in a timely fashion.

- However when hedonic procedures were tried on other component indexes they gave results which were *not noticeably different* from those of matched model indexes (see the National Academy of Sciences report on the CPI).

TV Example.

- there is 20% turnover over the sampling interval (almost identical rate to that in computers),
- we show below that there is ample evidence indicating that the goods that exit have prices that are falling disporportionately.

Yet when we compute a hedonic index based on a set of characteristics comparable to what the BLS analyst uses we get an index which is

- about the same value as the mm index (just as in NAS volume), and

- is more variant than the mm index.

(Come back to how we construct these.)

Table 1: **Matched Model and Standard Hedonic Indices.**[1]

Index Calculated	matched model	hedonic[3]	hedNP[3]
Panel A: Using Log-Price Regression Fit to All Observations			
hedonic uses S24[4]	-10.11	-10.21	n.c.
s.d. (across months)	5.35	7.53	n.c.
S24 % l.t. mm[2]		.50	n.c.
hedonic uses S9	-10.11	-8.82	-8.61
s.d. (across months)	5.35	7.05	7.88
S9[4] % l.t. mm		.40	.34

1. Implied rates of percent annual change (multiply the average monthly index by 1200). Averages are from May 2000 to January 2003. n.c. means not calculated: there were too many regressors for nonparametric calculation to be meaningful.
2. % l.t. mm= percentage less than matched model.
3. hedonic is linear, hedNP is local-linear kernel (bandwidth from cross-validation).
4. S24 is a regressor set comparable to that used by the BLS in their *once* a year hedonic. Could not be updated every period in production mode. S9 described below and could be updated.

This paper.

- Explains why hedonics might not perform differently than matched model indices despite the fact that exiting goods are goods whose prices are falling.
- The reason implies that standard hedonic procedures are inadequate.
- We then provide a modified hedonic procedures which takes account of the relevant phenomena, and
- Apply the modified procedures to the BLS's TV data set.
- Modification: yields an index that falls at a more rapid rate than the earlier hedonic or mm indices (look more like the rate we obtained for hedonics on computers).
- The modified index can be computed within the BLS's time constraints for a "production mode" index.

Annual Computer vs Bimonthly TV Data: Some Differences.

Unobserved Characteristics.

- Most of our TV characteristics are dummy variables indicating the presence or absence of advanced features.
- Exit is disproportionately of high priced goods that have most of these features. They exit because they are obsoleted by newer high priced goods with higher quality versions of the same features.
- There are no cardinal measures for the quality of these features.
- As a result in the TV market, and we suspect in many other markets, selection is partly based on characteristics the analysts can not condition on, i.e. on what an econometrician would call "unobservables".
- Possible Alternative: use good-specific "fixed effects" to account for unobserved character-

istics. I.e. use coefficients from a regression for the differences of log prices of continuing goods to predict the change in the market's evalution of the observed characteristic for the exiting goods.

- Problem: many unobservables and like other characteristics their regression coefficients change over time. So fixed effects do not either
  - control for the unobservables when obtaining the change in coefficients of observable, or
  - control for changes in the contribution of unobservables per se.
- **Goal:** Develop procedure which:
  - accounts for unobserved characteristics
  - maintains the bound, and
  - is robust to assumptions and data sets.

Other Properties of Data.

Sticky Prices.

- 75% of price comparisons are bimonthly and on average 60% of the prices do not change between readings (are "sticky").
- "About to exit" goods are systematically less sticky than most: goods that are exiting are in a part of the characteristic space which is changing quickly.

Large Price Variance.

- Enormous price variation (from \$66 to over \$10,000), reflects differences in products that the BLS includes in this commodity group.
- As in most markets, the entry and exit of particular TVs tends to disproportionately influence, and be disproportionately influenced by, prices of close competitors.
- Try to use local-linear nonparametrics to insure that the hedonic predictions for one good are not overly sensitive to goods which are in

very different parts of the product space, but limited by sample size.

Timeliness of Our Procedures.

Importantly our procedures enable us to use only a small number of ”easy-to-clean” product characteristics in the hedonic regression. As a result the combination of

- computerized data gathering, and
- our method

should enable the BLS to compute the indices we propose within their time constraints.

Are Goods that Exit Goods Whose Prices Are Falling?

Divide into three groups

- About to exit goods (a-exit): last price relative of good.
- Recently new (r-new): first price relative for the good.
- Continuing goods.

"a-exit" Evidence. "Similar" to goods that do exit and have;

- twice the rate of price fall (t-value ≈ 5.5),
- a significantly larger fraction of non-sticky and falling prices (all s.e.'s $\leq .014$), and
- an even larger price fall conditional on not-being sticky.

Table 2: **Price Relatives.**

Variable	Full Sample.	a-exit	r-new	contin.	exit-cont	new-cont
mean	.9849	.9729	.9844	.9881	-.0152	-.0037
(s.d. of mean)	(.0010)	(.0024)	(.0019)	(.0014)	(.0028)	(.0023)
cross-section s.d.	.0677	.0778	.0606	.0646	n.r.	n.r.
Fraction of Subsample With Relatives						
Equal 1 (or "sticky")	.6155	.5390	.6203	.6380	-.0990	-.0176
Greater than 1	.1166	.1097	.1142	.1213	n.r.	n.r.
Less than 1	.2679	.3513	.2655	.2407	n.r.	n.r.
# of obs.	5320	1167	1335	2818	n.r.	n.r.
Among Price Relatives Not Equal to 1 (i.e. not "sticky").						
mean	.9622	.9460	.9608	.9682	-.0222	-.0074
(s.d. of mean)	(.0024)	(.0056)	(.0049)	(.0034)	(.0063)	(.0058)
cross-section s.d.	.1039	.1083	.0920	.1024	.0059	-.0104
# of obs.	2017	549	514	1067	n.r.	n.r.

Using One Quarter of Sample with Monthly Price Quotes				
variable	All Monthly Data 2-month	a-exit 2-month	Exit month 2 month-1	Exit in 2: Square month-1
mean price relative	.9835	.9679	.9756	.9518
(s.d. of mean)	(.0016)	(.0036)	(.0068)	(.0136)
sticky price rate	.6569	.5776	.6270	.3931
# of obs.	1428	334	207	207

3/4 of price quotes are resampled at a two-month interval and 1/4 at a one month level.
We calculate a two-month index using all data.

Note: Absent period effects we would expect faster rate of price decline and less stickiness in year of exit (year the change in valuations were large enough to induce exits). To see if this is the case look to monthly subsample, and consider *first-month behavior of goods that exit in the second month of a two-month interval.*

Monthly Sample.

- **One month** price decline of goods that exit in month two is higher than two month price decline of continuing goods, and nearly the same as **two month** price decline of about to exit goods
- one month sticky price rate is lower than two month sticky price rate of continuing goods.

Conclude. Exiting goods have price declines that are greater (in absolute value) then those of continuing goods.

Table 3: **Log Prices on Dummies for Entering and Exiting goods.**

Specification	Constrained OLS		Minimum Distance	
	exit	new	exit	new
1. S0 (Odd)	.106	.161	.075	.146
(t-value)	(2.66)	(4.14)	(1.94)	(3.86)
2. S0 (Even)	.121	.133	.097	.130
(t-value)	(3.17)	(3.53)	(2.61)	(3.51)

Do goods that exit have low Prices?

Regress log prices onto dummies for newly enterred (25%), and exiting goods (22.5%).

- **Both** enterring and exiting goods have significantly higher prices than continuing goods, though the price differences are larger for new goods.
- Turnover in this market is at the high end (unlike computers).

Hedonic Regressions on Levels.

Characteristics Sets.

- S4: Quadratic in screen size and dummy for projection.
- S9=S4 + dummies for picture-in-picture, flat-screen CRT display, HDTV-ready, a high-quality Brand, and a low-quality Brand.
- S24: S9+ fourteen more dummies for presence or absence of other advanced features.

S9 is relatively easy to clean, S24 is not.

Fits. Recall that we need *separate regressions for each period.* Report mean adjusted R^2.

- S4 and linear .893
- S9 and linear .953.
- S24 and linear .967.
- S9 and local-linear kernel .963.

S9 seems to do fine, especially local-linear, and is easy to use in a production setting.

Note.

- Fits show; (i) that in *a given period* TV's with advanced features sell for alot more and (ii) a machine with the S9 features will generally have most of the S24 features.
- Other than screen size all characteristics in S9 are dummies, most for presence or absence of advanced features. In particular *no measure of quality* of the advanced features.

Does the Data Indicate We Should Worry About Unobserved Characteristics?

- Under standard assumptions if there were no unobserved characteristics that consumers care about, the price function for a-exit, r-new and continuing goods should be the same (this assumes full information, one good per firm, ..., or else a "dense" product space).
- No unobserved characteristics $\Rightarrow \quad R^2 = 1$, and it is not. However residual is small part of price variance and may be measurement error (though the price variance is large).
- Can we tell whether we should worry about residual variance?

One Test. See if the regression function of observed characteristics is the same for continuing, exiting, and new goods. If selection is based on the residual in an important way, regression function for continuing goods and exiting goods should be different, In particular goods which continue with observed characteristics which did poorly (were re-evaluated downward) should have had unobserved characteristics which do well (were re-evaluated upward) and v.v.

- Tests reject equality of coefficients.
- The corrleation of the change in the observed and unobserved components of price for the continuing goods was -.53.

Table 4: **Testing for Exit and New Good Interaction Terms.**

Test	$j = x$; F-test	$j = n$; F-test	$j = x$; Wald-test	$j = n$; Wald-test
Fraction Significant At Different α Levels*				
$\alpha = .01$	.14	.11	.50	.54
$\alpha = .05$	.29	.21	.71	.71
$\alpha = .10$	.46	.29	.79	.75

x=exiting and n=newly enterred interactions.
F-test assumes homoscedastic variance-covariance,
Wald-test allows for heteroscedastic consistent covariance matrix.

Second Test. Are residuals for exiting goods either lower, or falling at a faster pace, then those for continuing goods?

Level of disturbances.

- The residuals for goods in the period before they exit are lower, but not significantly so.

First differences of disturbances.: Table 5.

- Even for continuing goods they are negative (the unobserved characteristics of all goods are being obsoleted).
- a-exit goods have residual changes in the year before exit that are five times as large (in absolute value) as those of continuing goods.
- Conclude
  - Contributions of omitted variables to price changes over time,
  - fixed effect treatment for unobservables will generate misleading results.

Conclude: Tests indicate we should be worried about unobserved characteristics, and that a fixed effect correction is not sufficient.

Table 5: **First Difference Disturbances for About to Exit, Recently Entered, Goods.**

Variable	All Continuing	a-Exit	r-New	Remaining Goods.
Using the S9 Specification for the Hedonic Regression.				
mean	-.0028	-.0150	-.0050	-.0021
s.d. of mean	.0017	.0028	.0025	.0021
s.d.(across months)	.0091	.0151	.0132	.0113
percent < 0	.6207	.8621	.5517	.6552
Using a Local Linear Kernel Regression for the Hedonic[1].				
mean	-.0023	-.0133	-.0026	-.0025
s.d. of mean	.0015	.0023	.0024	.0017
s.d.(across months)	.0081	.0126	.0130	.0093
percent < 0	.6897	.7931	.6552	.6552

Correcting For Selection Using Only Bimonthly Data.

Step 1: Pricing equation.

$$p_{i,t} = h_t(z_i) + \eta_{i,t}.$$

- observed characteristics (z_i) contant over time, but function changes.
- "unobserved characteristic" is really a weighted average of characteristics and weights should be allowed to change over time.

Step 2: Bounding the change in the evaluation of unobservables.

Let $j = x, c$ index exiting and continuing goods respectively. To bound price changes for goods that exit we need an upper bound for

$$E[\eta_{t+1} - \eta_t | z, \eta_t, j = x].$$

To obtain the bound we need a model for exit.

Exit model. Goods continue iff their continuation value is positive. Formally

$$CV(\eta_i, z_i, \eta_{-i}, z_{-i}) \equiv CV_{\eta_t, z_t}(\eta_i, z_i) > 0.$$

Assume: Continuation value is monotone increasing in η. If no dynamics in demand or cost, and equilibrium is Nash in prices, this just says price increases in η more than marginal costs. More generally the increasing difference between price and marginal cost for higher quality goods justifies their development cost.

Assumption 1 (Exit Rule.)

$$j_{i,t} = c \quad \Leftrightarrow \quad \eta_{i,t+1} \geq \underline{\eta}_{t+1}(z_i). \qquad \spadesuit$$

That is a good with observed characteristics z exits only if $\eta_{i,t+1} \leq \underline{\eta}_{t+1}(z_i)$. We place no restrictions on $\underline{\eta}_{t+1}(z_i)$, and let it differ freely from period to period.

Implication.

$$E[\eta_{t+1} - \eta_t \mid j = x, z, \eta_t] =$$
$$E[\eta_{t+1} - \eta_t | \eta_{t+1} \leq \underline{\eta}_{t+1}(z), \eta_t, z]$$
$$\leq E[\eta_{t+1} - \eta_t | \eta_{t+1} \geq \underline{\eta}_{t+1}(z), \cdot]$$
$$= E[\eta_{t+1} - \eta_t \mid z, \eta_t, j = c] \equiv gb\Big(\underline{\eta}_{t+1}(z), \eta_t\Big).$$

This last expression can be estimated nonparametrically (as $\eta_{t+1} - \eta_t$ is observed when $j = c$).

Notes:

- Uses the fact that the value of the unobserved characteristics of all goods are falling over time to get bound on fall of unobserved characteristics of exiting goods.
- Adds another source of "non-tightness" of bound (unobserved characteristics for exiting goods are likely falling at a faster rate than this).
- Paper shows that you can add the assumption that the stochastic process generating η_t

is Markov and independent (instead of just mean independent) of z and derive a tighter bound. However we find tighter bound is sensitive to assumptions and to details of estimation algorithm, and hence we discard it.

How well do we do in predicting $\eta_{t+1} - \eta_t$ for continuing goods?

- About 10% of the variance in it is accounted for by z and about 20% when we add η.
- Implies there is selection on η_t (recall these are residuals from a projection, so otherwise $E[\eta_{t+1} - \eta_t | z] = 0$ "by construction").
- η_t greatly helps prediction for continuing goods (implies we are not dealing with a fixed effect or a martingale in selected sample).

Table 6: **Predicting $\eta_{t+1} - \eta_t$ for Continuing Goods.**

r.h.s.	z		(z, η_t)		(z, η_t), r-New.	
Goods/Mean	R^2	Adj. R^2	R^2	Adj. R^2	R^2	Adj. R^2
all continuing	.15	.10	.27	.18	.28	.19
nonsticky-only	.16	.04	.43	.20	.47	.21

Hedonic prediction for goods that exit.

$$p_{i,t+1} = h_{t+1}(z_i) + gb\Big(\underline{\eta}_{t+1}(z_i), \eta_{i,t}\Big) + \eta_{i,t}$$

and substitute estimated values.

Note. For efficiency reasons $gb(\cdot)$ is estimated from

$$gb(z_i, \eta_{i,t}) =$$

$$\sum_{q \in \{\Delta, s\}} E[\eta_{i,t+1} - \eta_{i,t} \mid q, j_{i,t} = c, z_i, \eta_{i,t}] Pr\{q \mid j_{i,t} = c, z_i, \eta_{i,t}\}$$

$$= E[\eta_{i,t+1} - \eta_{i,t} | q = \Delta, j_{i,t} = c, z_i, \eta_{i,t}] Pr\{q = \Delta | j_{i,t} = c, z_i, \eta_{i,t}\}$$

$$+ [p_t - z_i\beta_{t+1} - \eta_{i,t}]\Big(1 - Pr\{q = \Delta | j_{i,t} = c, z_i, \eta_{i,t}\}\Big).$$

I.e. we estimate the probability of price change, and use the exact $\eta_{t+1} - \eta_t$ for those whose prices do not change.

Corrections That Use Monthly Data.

The monthly data contains the actual price changes in the first month of the two month sampling period for about half of the exiting goods (the "late exits" or those that exit in the second month).

Table 7: **Monthly Data.**

Data for First Month of Two Month Period.		
	exit in second month	continuing goods
1. Fraction Sticky	.584	.756
2. Average Price Relative	.973	.993
3. Av. if P change in month 1	.933	.974
Two-Month Price Relatives for Continuing Goods.		
Change price in month 1?	*yes*	*no*
4. Average Price Relative	.969	.988

Data for first month.

- Price falls and fraction non-sticky for first month for goods that exit in the second month are greater than two month price falls and fraction non-sticky for goods that continue.

Two month data for continuing goods.

- Goods that continue but had a price change in the first month had a larger rate of price deflation.

Integrating The Monthly Information in Our Predictions.

Adaptation of Assumption 1. Condition on z. Then those that exit in the first month have unobserved characteristics whose value fell at a faster rate than those who survived the first month but exited in the second month. Formally, let $j^- = x$ ($j^+ = x$) denote the event that the good had exited by the end of the first (second) month of the sampling period, then

$$E[\eta_{i,t+1} \mid j^+_{i,t} = x, j^-_{i,t} = c, z_i, \eta_{i,t}] \geq$$
$$E[\eta_{i,t+1} \mid j^+_{i,t} = x, j^-_{i,t} = x, z_i, \eta_{i,t}],$$

and estimate a bound for the l.h.s. of this inequality.

Computation of bound (theory).

$$E[\eta_{t+1} \mid j_t^+ = x, \eta_t^+, j_t^- = c, z, \eta_t]$$

$$= E[\eta_{t+1} - \eta_t^+ \mid \jmath_t^+ = x, \eta_t^+, j_t^- = c, z, \eta_t] + \eta_t^+$$

$$\leq E[\eta_{t+1} - \eta_t^+ \mid \jmath_t^+ = c, \eta_t^+, j_t^- = c, z, \eta_t] + \eta_t^+$$

- Estimate last equation from the goods that survived both subperiods of the monthly data.
- Average over the distribution of $\eta_{i,t}^+$ conditional on $(j_{i,t}^+ = x, j_{i,t}^- = c, z_i, \eta_{i,t})$, a distribution which is available in the data.
- Use those averages to predict $\eta_{t+1} - \eta_t$ for the goods that exit in the bimonthly data.

Problem. The monthly sample is only 25% of the bimonthly sample, and only 10% of this sample can be used for the distribution of $\eta_{i,t}^+$ conditional on $(j_{i,t}^+ = x, j_{i,t}^- = c, z_i, \eta_{i,t})$. Consequently when we proceeded as above we got results that were imprecise and sensitive to included interaction terms.

Alternative. Restrict the difference in regression functions for $\eta_{t+1} - \eta_t$ for those who exit and those who do not to be just in the constant term. Formally

- use the regression of $\eta_{t+1} - \eta_t^+$ and the value of $\eta_t^+ - \eta_t$ to predict $\eta_{t+1} - \eta_t$ conditional on z and η_t for the late exits (a bound on the prediction equation for $\eta_{t+1} - \eta_t$ for all exits).
- Use this equation to construct predicted $\eta_{t+1} - \eta_t$ to form the bound for all exits in the bimonthly sample,
- Add a 0-1 variable to the right hand side of the regression predicting $\eta_{t+1} - \eta_t$ in the bimontly sample, which takes the value of one when the observation was from the prediction.

We did this with and without weighting the exiting observations differently, and with an assortment of right hand side interactions and the answers were quite stable.

An Alternative Assumption and a Robustness Test.

Assume

- change in the exiting good's price in the period in which it exits is, on average, at least as negative as it was for the same good in the period prior to exit (as the exiting period is when obsolescence is likely largest).

Alternative index:

- When price change in the period before exit is available (about 85% of the goods that exit between t and $t+1$) use it for the unobserved price change in the exiting period.
- The other 15% enterred between $t-1$ and t and then exited before $t+1$. For this latter group of goods we use one of our other bounds.

Results: Models With Selection Corrections.

Use Only Bimonthly Data.

- Hedonic with fixed effects to account for selection:
  Result=-10.66% (5.4% correction).
- Hedonic with selection model (non-parametric): Result = -11.6 % (10.5% correction), and the standard deviation across months goes down alot (it is now lower then that of the mm)

Use Also Monthly Data.

- Use observed price changes in first month of goods that exit in the second month, and price changes for the second month of goods that continued.
  Result=-12.51 (24% correction).

Note. As we start using the monthly sample more intensively we get larger standard deviations across months. May or may not worry about this. First it may be true, or it may be sampling and estimation variance. Second even if it is sampling or estimation variance the CPI averages over many of these component indexes.

Table 8: **Alternative Monthly Indexes for TV[1].**

Index Calculated	matched model	hedonic	hedNP
Bimonthly Data Only.			
Panel A: Fixed Effects (in logs) Selection Correction.			
mean	-10.11	-10.62	-10.40
standard deviation	5.35	5.79	6.43
% l.t. mm		.70	.66
Panel B: Non-Parametric Selection Model.			
mean	-10.11	-11.17	n.c.
standard deviation	5.35	5.01	n.c.
%l.t.mm		.80	n.c.
Using Monthly Data.			
Panel C: Probabilities and Price Changes.			
mean	-10.11	-12.51	n.c.
standard deviation	5.35	7.94	n.c.
%l.t.mm	n.c.	.83	n.c.

1. See the footnotes to Table 1. All indices use S9 regressor set and the data referred to in earlier table. n.c.=not calculated.
2. % l.t. mm = percentage less than matched model; standard deviation is standard deviation of the index across months.

Robustness.

- Using about to exit values where they are available, and hedonic predictions when not, gives a correction of over 20%.
- I.e. we get faster rate of decline then our prediction that uses only the fall in prices of continuing goods, but not as fast as one that uses price changes in the (first month of) the period they actually exit – just as one would have predicted if obsolescence was greatest in the period of exit.
- Note also that the standard deviations across months are now comparable to those of the hedonic.

Table 9: **Robustness Analysis.**

A-Exit Price Changes If They Exist and Panel ? Last Table Otherwise		
Index Calculated	matched model	hedonic
Bimonthly Otherwise.		
mean	-10.11	-12.15
standard deviation	5.35	5.13
% l.t. mm		.83
Monthly Otherwise.		
mean	-10.11	-12.27
standard deviation	5.35	5.91
% l.t. mm		.93

Notes:
1. The average (over all months) fractions of goods that are continuing, exiting-with-a-previous-relative, and exiting-without-a-relative are, respectively, $(.793, .171, .036)$.

To Do List.

- Automate and run forward from 2003 (out of sample).
- Check for likely impact on CPI as a whole (as compared to current correction procedures), and impact of that on budget deficit.

Table 10: **Comparison Between Time Periods.**

Index Calculated	May 2000 January 2003	February 2005 November 2006
matched model	-10.11	-19.29
standard deviation	5.35	9.31
Hedonic With Adjustment for Unobservables.		
Bimonthly Adj.	-11.16	-20.44
standard deviation	5.35	10.95
Adj. to mm	1.05	1.15
Monthly Adj.	-12.51	-23.20
standard deviation	5.35	11.15
Adj. to mm	2.41	3.91
Pre-Exit with Hedonic Adj. When Not Available.		
Bimonthly Adj.	-12.15	-22.30
standard deviation	5.35	8.80
Adj. to mm	2.04	2.68
Monthly Adj.	-12.27	-22.69
standard deviation	5.35	9.34
Adj. to mm	2.17	3.40

Notes:
The later data drops the brand dummies and the "flat-screen" variable (as all tube TV's have flat screens by this time). It adds flat panel (LCD or plasma) and an interaction between screen size and flat panel. The hedonic adjusted R^2 in the later data was lower, averaging about .9.