Comparing Quality Adjustment Methods: A Case Study for Televisions in Japan*

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Abstract.

Using unique datasets we recently obtained, we conducted a what-if case study for the quantitative impact on the choice of alternative quality adjustment methods for television price indexes in Japan's domestic output price index, known as the Domestic Corporate Goods Price Index (DCGPI). We focus our analysis on the quality adjustment methods that are widely used among the PPI agencies in order to add some evidence in the research field of quality adjustment methods from a practitioner's perspective. The analysis shows that the choice of quality adjustment method significantly changes the image of the constant-output price of televisions.

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Introduction

Quality adjustment is one of the most delicate and difficult tasks for the world's statistical agencies. Practitioners might always ask themselves how significantly the index would differ if a different quality adjustment method was applied. In many cases, data limitations discourage practitioners from tackling this simple yet important question. Using unique datasets we recently obtained, we conducted a what-if case study for the quantitative impact on the choice of alternative quality adjustment methods for television price indexes in Japan's domestic output price index, known as the Domestic Corporate Goods Price Index (DCGPI).

To clarify the focus of the paper, we start by presenting a simple two-period relationship, a slightly modified version of that presented by Hulten [2003]:

$$\frac{\hat{P}_{0,1}^{F}}{P_{0,0}^{F}} \equiv \frac{P_{1,1}^{F}}{P_{0,0}^{F}} \times \left(\frac{P_{1,1}^{F}}{\hat{P}_{0,1}^{F}}\right)^{-1} \Leftrightarrow 1+\pi \equiv \frac{1+z}{1+x}, \tag{1}$$

where $P_{j,t}^{F}$ denotes the output (or factory-gate) price of product j at time t. The left-hand side of the equation, defined as $1+\pi$, denotes the (gross) rate of change in the output price index (or the rate of pure price change). The first term on the right-hand side, defined as $1+z$, denotes the (gross) rate of change in the measured price of two products. The second term, defined as $(1+x)^{-1}$, denotes the inverse of the (gross) rate of quality change between the two products.

When product 0 and product 1 are regarded to be different products in terms of their quality, the statistical agency needs to estimate x using some quality adjustment method. The statistical agency rarely observes $P_{0,1}^{F}$ on such occasions since firms are likely to switch their entire shipment from product 0 to product 1 all at once at the factory-gate level[1].

Equation (1) implies that the dynamics of π are purely driven by the estimated series of x for a given history of factory-gate prices, the timing of forced substitutions which requires quality adjustments, and the choice of succeeding replacements at the timing of forced substitutions. Thus, one can simulate and compare alternative indexes using different x estimated by different quality adjustment methods.

We focus our analysis on the quality adjustment methods that are widely used among the PPI agencies in order to add some evidence in the research field of quality adjustment methods from a practitioner's perspective[2]. Specifically, the following three types of direct quality adjustment method are analyzed[3].

The resource-cost method

The resource-cost method is traditionally the most popular quality adjustment

[1] This property explains some of the difference in developments between the PPI and CPI. See Bustinza *et al*. [2008] for an excellent summary of price measures for new vehicles.

[2] See Pakes [2003] for the hedonic method versus matched-model method or Diewert, Heravi, and Silver [2007] for the hedonic imputation method versus time dummy hedonic method.

[3] In the literature, the categorization of implicit/explicit rather than direct/indirect is popular. We define the *direct* method as the method using information of two products that are directly involved in the forced substitution. For example, the overlap method is usually defined as an implicit method, but we define it as a direct method in our paper since it uses the observed price information of product 0 and product 1 in the retail market. The class-mean imputation method, for example, is defined as an *indirect* method since it infers x using price information other than product 0 and product 1.

method of output prices. More than 20% of quality adjustments, including quality adjustments for televisions, rely on this method for Japan's DCGPI. To apply this method, the statistical agency asks the reporting firms how much it cost to produce the new product and how much it would have cost to produce the old product in the current period. The relative cost of the new product to the old becomes the estimate of the gross rate of quality change, $1+x$.

This method, if it works ideally, is known to be consistent with the construction of production-theoretic output price indexes. However, there exist several limitations for this method as mentioned by the International Monetary Fund [2004]. Most importantly, the reporting firms may not be able to answer the resource cost of the old product under the current-period production technology.

In a later section, we show the results of the conventional method which relies on the voluntary cooperation of reporting firms and the results of the newly-proposed method which involves a privately-sold resource-cost dataset offered by DisplaySearch LLC. See the Appendix for a description of the data.

The hedonic method

The hedonic method involves estimating the hedonic regressions which specify the functional relationship between the characteristics embodied in the products and the products' market price. The fitted value of regression is regarded as the implicit price of a product conditional on its characteristics. The gross rate of quality change 1+*x* is estimated by the ratio of the implicit price for the new product 1 to the old product 0 for PCs, Digital Cameras, Computer Printers, Copying Machines, Video Cameras, and Servers in Japan's DCGPI[4].

To calculate the hedonic index for televisions, we estimated ten hedonic regressions semiannually using the scanner data compiled by BCN Inc[5]. The estimated results are shown in Table 3, which will be discussed later[6].

The overlap method

The overlap method simply regards the difference in the measured prices of product 0 and product 1 as the measure of quality difference in the two products. Specifically, we define the active overlap method which infers 1+*x* by the observed relative price $P_{1,1}^{R}/P_{0,1}^{R}$, where $P_{j,t}^{R}$ denotes the retail price of product *j* at time *t*. This method exploits information on the relative prices of the two products that can be simultaneously observed in the retail market at the timing of forced substitution. The baseline retail price data we use for the following case study is the scanner data compiled by BCN Inc., which is also used for the hedonic estimation. The alternative

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[4] There are many approaches to estimate hedonic indexes as summarized and analyzed in Heravi and Silver [2007]. Following their terminology, the BOJ's method can be categorized as a variant of the hedonic current-period indirect price index.

[5] BCN Inc. gathers the daily Point of Sale (POS) data from 22 home electronics retailers in Japan.

[6] See Moulton et al. [1998] for the hedonic analysis in the US CPI. It reports that the four-year decline in the conventional index from August 1993 to August 1997 is 13.2 percentage points whereas the decline in the estimated chained hedonic index is 21.0 percentage points.

retail price data is obtained from the internet website operated by Kakaku.com, Inc. which provides surveys of the lowest price quotes for televisions sold on the internet.

Finally, we need to define the undesirable passive overlap method. This method regards the rate of change in the measured prices of two products, z, as the estimate of x. By definition, π stays zero at the timing of forced substitution when this method is applied. Passive overlap is chosen as the last resort when the BOJ is unable to adjust quality directly. For the television case, this method is chosen when reporting firms are unable or refuse to provide relevant resource-cost information for the two products. Also, the BOJ applies passive overlap when a reporting firm changes or the reporting format changes, for example, from absolute value to indexed value from the base point in time.

Table 1 summarizes estimators for x in each quality adjustment method. Here, $C_{j,t}^{conv}$ denotes the resource-cost information obtained from reporting firms for product j at time t and $C_{j,t}^{priv}$ denotes privately-sold resource-cost information for product j at time t. $\hat{P}_{j,t}^{hed}$ denotes the fitted value of hedonic regression given the characteristics of product j at time t.

Empirical results

The BOJ surveys monthly prices for eleven different models of televisions that are sold domestically in order to compile the 2005 base-year DCGPI. Currently, seven of the eleven models are the liquid crystal display (LCD) type and the other four are the plasma display panel (PDP) type. From January 2005 to December 2009, reporting firms requested 61 forced substitutions and the conventional resource-cost method (a), if applicable, is used on such occasions.

We apply four alternative quality adjustment methods to calculate four additional television indexes. The methods used are the alternative resource-cost method (b) using a privately-sold resource-cost dataset, hedonic method (c), active overlap method (d) using scanner data for retail prices, and active overlap method (e) using the lowest price quote on the internet.

Figure 1 shows five television indexes with different quality adjustment methods. All indexes except for index (e), which is available from September 2006 due to the data limitation, are normalized to 100 in the year 2005. The starting level of index (e) is set at the same level as index (d) in September 2006 so that the paths of index (d) and index (e), which rely on different sources of retail price information, are easily compared.

In December 2009, index (b) remains highest at 50.7 and index (d) sinks lowest at 17.7. The implied annual inflation rate for index (b) and index (d) is −12.7% and −29.3%, respectively. The divergence is quite large and the choice of quality adjustment method seems to have a critical impact on the evaluation of the inflation rate of the television index for Japan’s DCGPI.

Three additional implications are worth noting. First, developments in index (a) which applies the conventional method and index (c) which applies the hedonic method are surprisingly similar. The implied annual inflation rate for index (a) and index (c) is −16.6% and −15.4%, respectively. Second, the result is not consistent with the view that the hedonic method tends to yield unconventionally large estimates for quality improvement. Third, overlap method (d) using scanner data yields larger estimates for quality improvement compared to those estimated by method (e) using lowest price quotes on the internet. We will examine these issues in more detail.

Table 2 summarizes the sample statistics of the estimated rate of quality change *x*, the sole factor that explains the differences among the five indexes. The sample mean in the first row of the table is calculated by the following formula:

$$\bar{x} = \alpha \times \sum z + (1-\alpha) \times \sum \hat{x}, \qquad (2)$$

where α denotes the fraction of forced substitutions which are handled by the passive overlap method. z denotes the estimated rate of quality change handled by the passive overlap method and $\hat{x}$ denotes the estimated rate of quality change other than the passive overlap method.

As implied in Figure 1, $\bar{x}$ for method (d) is the largest and $\bar{x}$ for method (b) is the smallest among the five methods. This is partly because the dataset for the method (b) does not cover some important options for television such as HDD and it may underestimate the rate of quality change. The standard error in x for the passive overlap method is quite large, casting serious doubt on the credibility of the method. The fact that the largest α is observed for method (a) highlights the risk of the conventional method that fully relies on reporting firms' cooperative capability and willingness. For method (a), $\bar{x}$ for sub-samples which used the passive overlap method takes a large positive number, thus pushing up $\bar{x}$ for all samples. On the contrary, the fact that method (c) has the lowest α and that its $\bar{x}$ for all samples is mostly unaffected by $\bar{x}$ for the sub-samples may encourage more widespread use of hedonic regressions in the quality adjustment of output price indexes.

Table 3 shows the estimation results for the semiannual hedonic regressions. For the estimation, the dependent variable and independent variables other than dummy variables are all log-transformed. As shown in Figure 2, the results for the log-linear version and for the non-linear version using the Box-Cox transformation for each continuous variable show very little difference in the index.

This result has two interesting features. First, the dynamics of parameter estimates for many characteristics tend to show an inverse U-shape. That is, the parameter estimates for many characteristics tend to increase at the stage of introduction and decrease gradually at the stage of penetration to the market.

This dynamic might be naturally explained by Pakes' interpretation of hedonic regressions (Pakes [2003]). The marginal cost of producing some characteristics may decline due to technological innovation and the diffusion of such characteristics may additionally lower the markups of those characteristics over the medium to long term. This may well explain why the parameter estimates of many characteristics gradually decline.

The increase in characteristics at the introduction stage is a more difficult fact to explain. Expected markups conditional on some characteristics may increase when some technological innovation or externality improves the value of conditioned characteristics. For example, a digital tuner is irrelevant if no broadcaster shows digital TV programs. Once broadcasters start to show attractive digital TV programs, the expected markup for digital tuners will increase at the stage of introduction.

Second, the release-date dummies explain a significant portion of the differences in implicit prices between old and new televisions that have exactly the same characteristics. Figure 3 indicates the size of the mean and the median of the release-date dummy for ten regressions. On average, televisions released today are 15% more expensive than televisions with exactly the same characteristics released one year ago.

Since the hedonic method (c) neglects the release-date effect for the calculation of implicit prices, we can conclude that the release-date effect explains the major part of the differences in estimated x between method (c) and method (d) which use identical scanner data obtained in the retail market.

What is the real nature of the release-date effect? One possible candidate is the clearance sale effect which may push down the price of old products significantly from their implicit price. If this is the case, the release-date effect should be neglected for quality adjustment.

Another possibility is that hedonic regressions suffer the classical omitted variable problem. For example, the quality of televisions with the same size and the same options can differ greatly if they use intermediate materials, such as glass substrates or plastic films, with different quality. Furthermore, the quality of these materials improves as time goes by.

Additional evidence derived from the resource-cost dataset should not be overlooked. Using hundreds of resource-costs for matched specifications for size and resolution, we calculated the median inflation rate of the resource-cost for LCDs and PDPs, and found it was −18.3% for LCDs and −25.9% for PDPs. A linear combination of these figures using the actual sample share of Japan's DCGPI implies that the markup-constant price index for given characteristics falls by 21.1% per annum. Surprisingly, this figure falls in the middle between those estimated by method (c) and those estimated by method (d). In a future work, we need to tackle the "release-date puzzle" in a more sophisticated manner[7].

Figure 4 compares the size of relative prices used for method (d) and method (e) from the day of release of the new model. The figure shows that the relative price of

[7] Geske, Ramey, and Shapiro[2007] decomposed depreciation rate into three terms, namely Age-related depreciation, Age-zero depreciation and Obsolescence, to investigate why computers depreciate so rapidly.

scanner data is consistently larger than those observed on the internet. Moreover, the relative price sharply falls for the data observed on the internet. This result suggests that internet retailers may not be burdened by having to keep large amounts of old-model inventories compared to large retailers which provided the scanner data. In other words, data from the internet might be more immune to the clearance sale effect. The downward-sloping curve of the relative price on the internet, however, implies that the choice of timing of forced substitution substantially affects the estimated rate of quality adjustments.

Concluding Remarks

In this paper, we showed that the choice of quality adjustment method significantly changes the image of the constant-output price of televisions. Although we are still far from answering the ultimate question of which quality adjustment method should be used for compiling the output price indexes, the results of the present study suggest some important clues for making further progress. First, the frequency of using the undesirable passive overlap method can be significantly reduced if scanner data is available for quality adjustment. Second, unmasking the "release-date puzzle" may be necessary for more widespread use of scanner data in the quality adjustment of the output price indexes. Third, it is worth unifying the analysis for both the production side and the demand side. The results in this paper suggest that, in some cases, the resource-cost approach and retail price approach may reach similar quantitative conclusions.

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Table 1. Estimators for the Rate of Quality Chance (x) for Various Methods

Method	Estimator
(a) Conventional resource-cost[*1]	$C_{1,1}^{conv} / C_{0,1}^{conv}$ -1
(b) Alternative resource-cost	$C_{1,1}^{priv} / C_{0,1}^{priv}$ -1
(c) Hedonic	$\hat{P}_{1,1}^{hed} / \hat{P}_{0,1}^{hed}$ -1
(d), (e) Active overlap	$P_{1,1}^{R} / P_{0,1}^{R}$ -1
Passive overlap	$P_{1,1}^{F} / P_{0,0}^{F}$ -1($\equiv z$)

*1 In practice, the absolute resource-cost difference, not the ratio shown in the table, is frequently used for calculating the index for Japan's DCGPI.

$C_{j,t}^{conv}$: Resource-cost of product j at time t, provided by reporting firms.

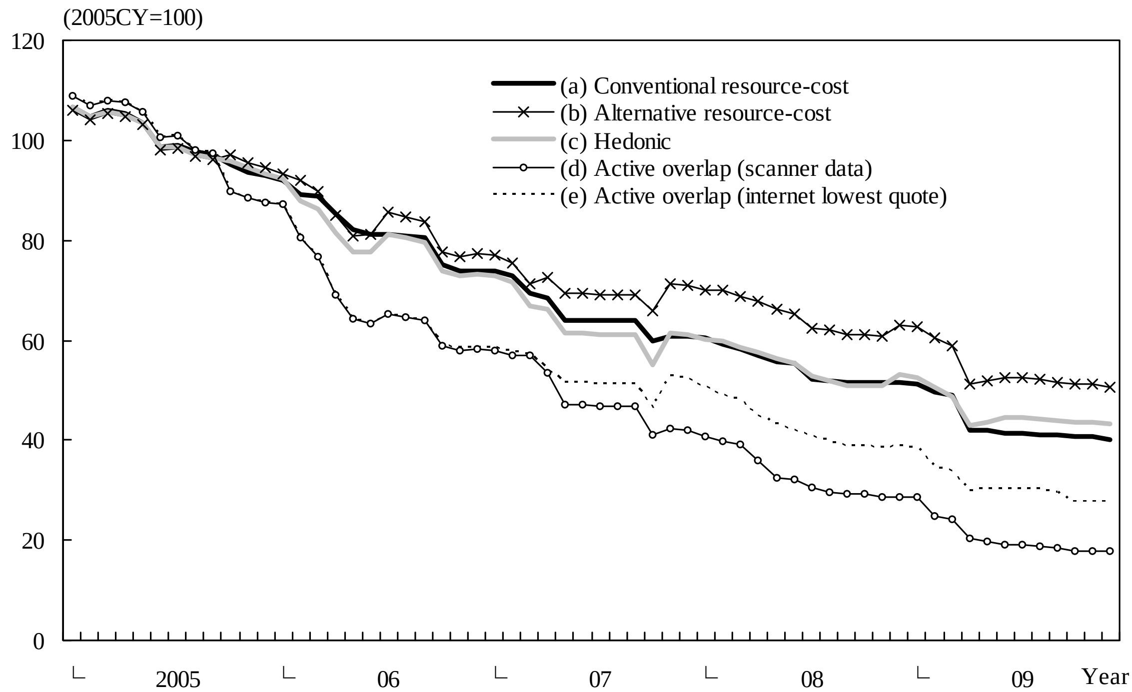
$C_{j,t}^{priv}$: Resource-cost of product j at time t, provided by a private professional firm.

$\hat{P}_{j,t}^{hed}$: Fitted-value of hedonic regression for product j at time t.

$P_{j,t}^{R}$: Retail price of product j at time t.

$P_{j,t}^{F}$: Factory-gate price of product j at time t.

Figure 1. Television Indexes using Alternative Quality Adjustment Methods



Data source: BOJ, BCN Inc., DisplaySearch LLC., and Kakaku.com Inc.

Table 2. Summary Statistics for the Estimated Rate of Quality Chance (x)

Method	Conventional resource-cost (a)	Alternative resource-cost (b)	Hedonic (c)	Active overlap Scanner data (d)	Active overlap Internet quote (e)
All samples					
Mean (%)	11.9	6.1	9.7	32.9	22.9
Std. deviation	52.3	48.5	50.4	60.9	64.4
Number of obs.	61	61	61	61	46
Fraction of forced substitutions handled by the passive overlap method					
alpha (%)	29.5	18.0	16.4	19.7	26.1
Sub-samples using the passive overlap method					
Mean (%)	21.1	13.5	3.5	-0.2	-0.2
Std. deviation	89.8	112.8	113.7	103.3	103.3
Number of obs.	18	11	10	12	12
Sub-samples using methods (a) to (e)					
Mean (%)	7.8	4.5	10.9	41.0	31.0
Std. deviation	19.9	16.2	26.7	42.9	42.9
Number of obs.	43	50	51	49	34

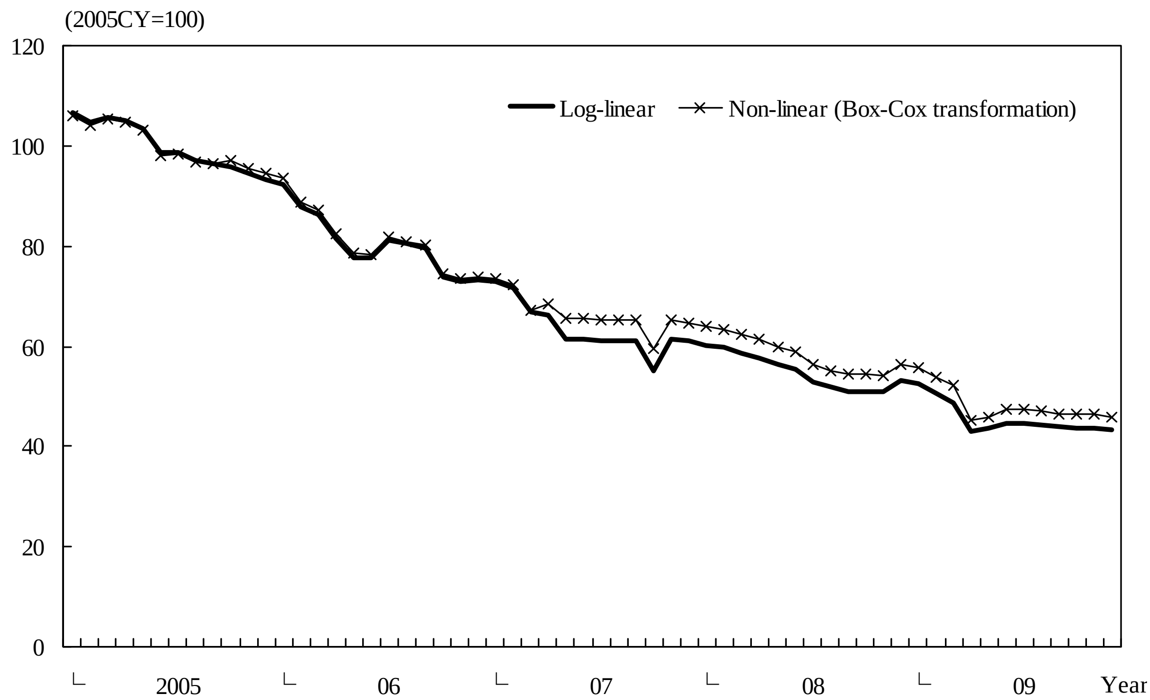
Data source: BOJ, BCN Inc., DisplaySearch LLC., and Kakaku.com Inc.

Table 3. Estimation Results for Hedonic Regressions

	1st half 2005	2nd half 2005	1st half 2006	2nd half 2006	1st half 2007	2nd half 2007	1st half 2008	2nd half 2008	1st half 2009	2nd half 2009
Intercept	4.665 ***	5.562 ***	4.792 ***	4.829 ***	4.754 ***	5.043 ***	4.707 ***	3.781 ***	3.132 ***	2.163 ***
TV size (inches)	1.598 ***	1.556 ***	1.502 ***	1.430 ***	1.249 ***	1.261 ***	1.217 ***	1.258 ***	1.299 ***	1.412 ***
Resolution (pixels wide)	0.284 ***	0.147 ***	0.278 ***	0.213 **	0.371 ***	0.314 ***	0.359 ***	0.488 ***	0.515 ***	0.602 ***
Built-in digital tuner	0.241 ***	0.342 ***	0.205 **	0.652 ***	--	--	--	--	--	--
PDP TV	--	--	0.083 *	0.147 ***	0.221 ***	0.181 ***	0.224 ***	0.140 ***	0.100 ***	--
120Hz refresh	--	--	--	--	0.171 ***	0.230 ***	0.242 ***	0.128 **	0.123 *	--
Built-in HDD	--	0.153 ***	0.118 ***	0.232 ***	0.229 ***	0.283 ***	0.337 ***	0.229 ***	0.173 ***	0.137 ***
Built-in BD	--	--	--	--	--	--	--	--	0.282 ***	0.391 ***
Internet-capable	--	--	--	0.210 ***	--	--	--	0.178 ***	--	--
LED-backlight	--	--	--	--	--	--	--	--	0.563 ***	0.263 **
Built-in PC card slot	--	0.136 ***	--	--	--	--	--	--	--	--
Built-in SDHC slot	--	--	--	--	--	--	--	--	0.128 **	--
Maker dummy										
Sharp	0.090 ***	0.167 ***	0.149 ***	0.249 ***	0.223 ***	0.211 ***	0.262 ***	0.193 ***	0.259 ***	0.109 **
Sony	--	0.084 ***	--	0.138 ***	0.134 ***	0.116 ***	0.180 ***	--	0.284 ***	0.217 ***
Panasonic	--	0.074 **	0.103 ***	--	0.209 ***	0.222 ***	0.239 ***	--	0.165 **	0.214 ***
Pioneer	--	--	--	0.284 ***	0.297 ***	0.563 ***	0.780 ***	0.770 ***	0.830 ***	--
Mitsubishi	-0.204 ***	--	--	--	--	--	--	-0.155 *	-0.158 *	--
Toshiba	--	--	--	--	--	--	--	-0.159 ***	--	--
Release date dummy (t = Release date)										
t-1	-0.005	-0.090 **	-0.006	-0.034	0.087	0.052	-0.012	-0.056	-0.064	-0.014
t-2	0.037	-0.062	0.128 **	-0.153 ***	0.058	-0.092	0.043	-0.145 ***	-0.070	-0.035
t-3	0.015	-0.123 ***	-0.093 **	-0.134 **	0.008	0.019	-0.049	-0.207 ***	0.012	-0.128 *
t-4	-0.028	-0.191 ***	-0.122 ***	-0.189 ***	-0.157 ***	-0.048	-0.237 ***	-0.134	-0.125 **	-0.237 **
t-5	-0.095 **	-0.144 ***	-0.151 ***	-0.181 **	-0.160 ***	-0.071	-0.014	-0.360 ***	-0.288 ***	-0.043
t-6	-0.154	-0.213 ***	-0.174	0.306 ***	-0.051	-0.431 **	0.097	-0.355	-0.171	-0.123
t-7	-0.255 ***	-0.104	-0.102	-0.060	-0.100	--	-0.037	--	--	-0.435 **
t-8	-0.099	--	-0.172	0.197	-0.111	--	--	--	--	--
t-9	--	--	-0.028	--	--	--	--	--	--	--
t-10	-0.160	--	--	0.173	--		--			--
Adjusted R-square	0.981	0.982	0.963	0.965	0.942	0.940	0.925	0.955	0.943	0.915
Number of observations	106	110	125	116	136	128	131	108	142	113

Data source: BCN Inc. ***, **, *: Significant at 1%, 5%, 10%.

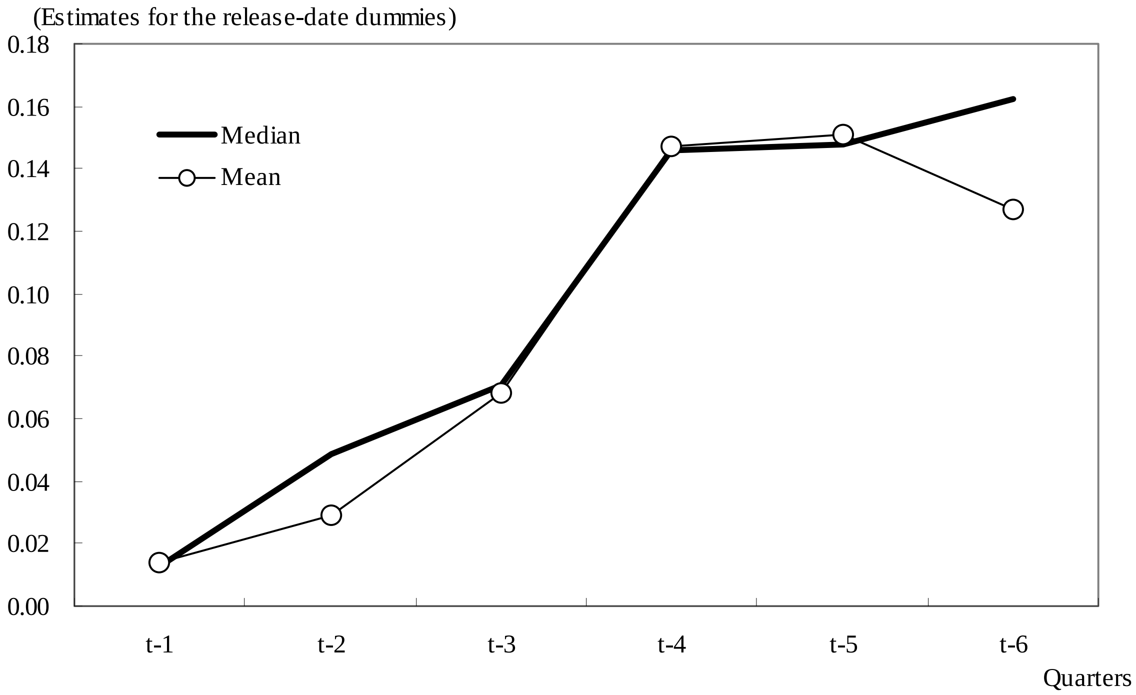
Figure 2. Television Indexes Using Log-linear and Non-linear Hedonic Regressions



Data source: BOJ, BCN Inc.

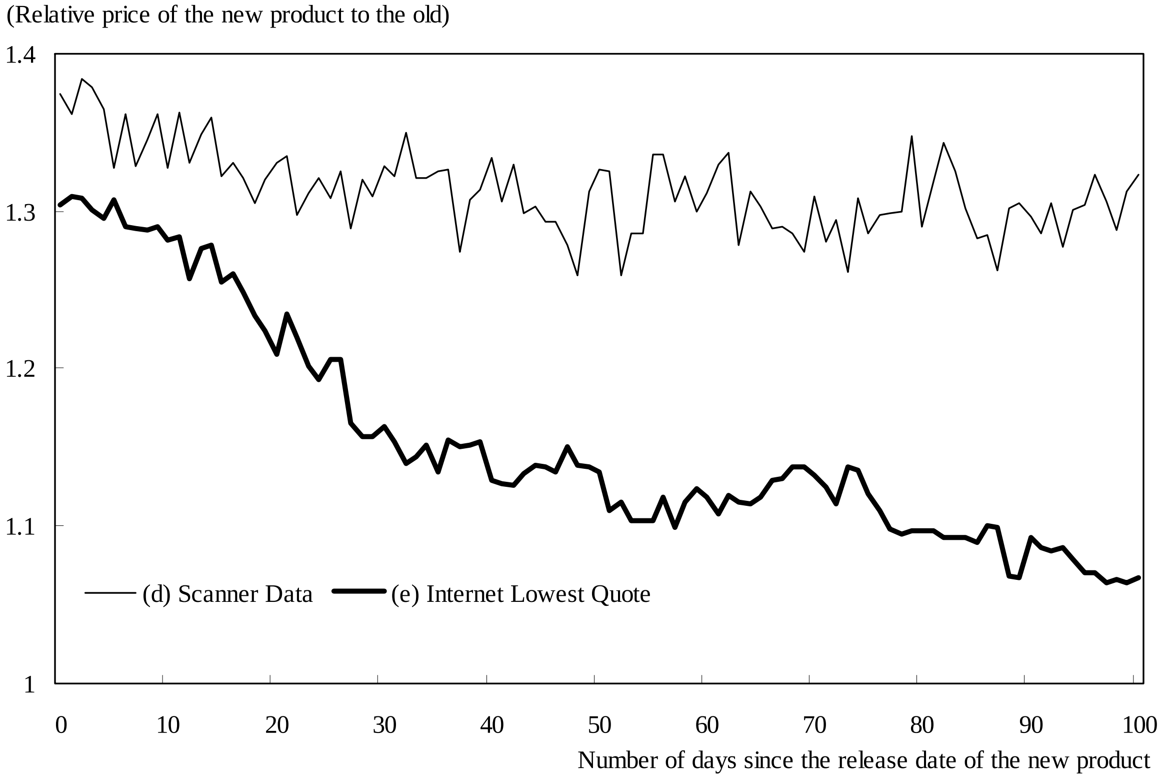
Note: Log transformation is applied to all variables except for dummies for the log-linear estimation. The Box-Cox transformation, $x_i^{\text{Box-Cox}} = (x_i^{\lambda_i}-1)/\lambda_i$, is applied to all variables i except for dummies for the non-linear estimation.

Figure 3. Estimated Release-Date Effects in Hedonic Regressions



Data source: BOJ, BCN Inc.

Figure 4. Dynamics of Relative Prices in the Retail Television Market



Data Source: BCN Inc., and Kakaku.com Inc.

Note: Relative price is defined as $P_{1,t}^{R}/P_{0,t}^{R}$ where $P_{j,t}^{R}$ denotes the retail price of product *j* at time *t*. We calculate the median of relative prices for all products that experienced forced substitution from the day of the release of the new product since September 2006. Due to data limitations, the sample size varies from 26 to 35 for the scanner data and 36 for the lowest quote on the internet, respectively.

Appendix

The dataset we used for the alternative resource-cost method is a customized version of "Quarterly LCD (PDP) Cost and Price Forecast Model Report," supplied by DisplaySearch LLC. The dataset contains major parts costs, as well as other production costs such as labor and warranty for each model by quarter. The five-year dataset we received contained 314 samples for 35 types of LCD and 222 samples for 16 types of PDP. Table A shows an example of the resource-cost share. The table indicates that the LCD module accounts for more than 60% of the resource cost.

Table A. Resource-Cost Share in 2008 Q4 (For LCD, 32-inch, 1366x768 pixels)

	(%)
LCD Module (size, resolution)	62
Other Mechanical (teletex circuitry, cables)	6
Labor	5
Other Electronics (backcover, bezel, stand)	5
Image Processing	4
Power	3
Packaging & Accessories	3
Warranty	2
Royalties	2
Handling & Surface + Freight to USA	2
Audio Processing	2
ATSC Tuner	1
PCB Mechanical	1
Insurance	0
USA Import Duty	0

Data source: DisplaySearch LLC.

Several limitations should be noted when applying the dataset to the analysis of production cost in Japan. First, the assumed specifications are basically those for the Advanced Television Systems Committee model in the U.S. Second, costs are expressed in U.S. dollars; we applied the market exchange rate to convert them into yen. Third, the assumed specifications may not be consistent for all brands and all models; DisplaySearch claims that it just uses conventional OEM models as the evaluation base. Fourth, the dataset does not cover some important options such as HDD.