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Toward Improving Quality Adjustment in Price Statistics: Empirical Evidence Supporting So-called *50 Percent Rule*[*]

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Abstract
In this paper, we examine pricing patterns over the product life-cycle and quality growth at the time of product turnover regarding a wide range of durable consumer goods sold in Japan. Applying hedonic regressions with time dummies to large granular data sets obtained from *Kakaku.com*, a well-known price comparison website in Japan, we find out some path-breaking empirical evidence for the existing quality adjustment method in price statistics, so-called *50% rule*, which has been implemented by some statistical agencies. Our findings bring significant implications for improving quality adjustment methods under uncertainty of quality evaluation and lead to the better understanding of the firms' price setting behavior.

Keywords: price index, quality adjustment, price setting, hedonic approach

1. Introduction

The price index is constructed by indexing the price of goods and services with the price at the base point in time as 100. The index is created by selecting representative products in the market and surveying their prices continuously each period. If a representative product shifts from the old product to the new product, the target product for the price survey is changed without delay.

The price index captures changes in the price for the product with the same quality. Therefore, if there is a difference in quality between new products and old products, the index reflects the residue after subtracting the price difference due to the difference in quality from the whole price difference between new products and old products. This is the process of quality adjustment which is essential in compiling the price index.

[*] This paper is a short and preliminary version of Abe, Ito, Munakata, Ohyama, and Shinozaki (2016).

However, it is not always easy to quantify the degree of quality growth of new products accurately when implementing a quality adjustment at the time of product turnover. For this reason, some price statistics agencies have applied a simple quality adjustment method to regard 50% of the price difference between new products and old products as the quality improvement part when hidden price increase is suspected along with the quality growth of a new product but its magnitude is not known (so-called *50% rule*). In Netherlands, Hoven (1999) explains the 50% rule has been applied for electrical household appliances and hi-fi equipment if some concealed price increase is assumed. Similarly, as Dalen and Tarassiouk (2013) argues that Statistics Sweden makes the quality adjustment based on the 50% rule for transport equipment excluding cars when no relevant information is available for applying other quality adjustment methods. Based on Hoffmann (1999), the 50% rule was available as the second-best way to conduct the quality adjustment among the Federal Statistical Office of Germany prior to 1997. In the past, Ohta (1977) has proposed to use the 50% rule for the quality adjustment based on the principle of risk minimization under uncertainty where we do not know the qualities of products well.

The 50% rule that has been proposed or adopted in the above-mentioned countries, however, is not sufficiently supported either theoretically or in practice. Accordingly, in this paper, we examine the appropriateness of the 50% rule empirically by targeting at individual products of durable consumer goods sold in Japan. With this aim, we measure the *pricing patterns* of how the price of a product changes over its product life-cycle and the *quality improvement ratio* (QIR) so as to see how much the quality growth of a new product over an old one can explain their price difference. In the analysis, we will use large data sets of as much as about 5.6 million cases which are stored by *Kakaku.com*, a well-known internet price comparison site in Japan.

2. Empirical Analysis

2.1. Data Sets

In order to conduct the analysis, the data sets need to include consistent and comprehensive information on various specifications of products, which are necessary to develop a high quality estimation model, as well as the information on frequently revised prices, which allows us to accurately capture the price transitions. For that reason, we obtained (i) the data from

Kakaku.com on product specifications of consumer durables which were registered at its website between December 2012 and December 2015 and (ii) the data from *Kakaku.com Trend Search Enterprise Edition*, a paid marketing support service operated by Kakaku.com, Inc., on the average price of individual products with weekly frequency from December 2013 to December 2015; and by integrating both, we developed unbalanced panel data sets for our analysis needs.

The data sets consist of eight commodities of home electrical appliances and twelve commodities of digital consumer electronics. The number of products included in the data sets is about 4,500, while the size of panel data multiplying the number of products and the number of data periods corresponding to each product is about 150,000. Moreover, the so-called volume of total data—which are obtained by multiplying the size of panel data and the number of specification data corresponding to each product—is huge at over about 5.6 million.

2.2. Estimation of Hedonic Functions

In the empirical analysis, we will estimate the following hedonic functions which incorporate dummy variables to control the elapse of time from the launch of products so that we can capture the effect of price transition through the life-cycle of products.

$$\ln(p_{i,t}) = \alpha + \sum_k \beta_k X_{i,k} + \sum_\tau \gamma_\tau D_t(\tau_i + \tau) + \sum_\tau \delta_\tau D_t(\tau) + \varepsilon_{i,t} \qquad (1)$$

$$\text{where } D_t(T) = \begin{cases} 1 & (\text{if } \ t = T) \\ 0 & (\text{if } \ t \neq T) \end{cases}$$

where $p_{i,t}$ represents price of product i at time t, while $X_{i,k}$ shows kth specification of product i. $D_t(\tau_i + \tau)$ and $D_t(\tau)$ mean the dummy variable to control the number of elapsed weeks from the launch of each product at τ_i, and the dummy variable to control macroeconomic shocks in each quarter during the data period, respectively. $\varepsilon_{i,t}$ is an unobserved random disturbance term.

Specifications of each product include both of those which are expressed as continuous values and those as dummies. In order to secure the comparability among commodities, this paper will use the common form of functions for all commodities in terms of formulation of the data. In this vein, we have conducted regressions specified in both semi- and double-logarithmic forms and we concluded that the semi-logarithmic form was superior in terms of log-likelihood values.

The LSDV (Least Square Dummy Variables) estimation has been applied in the analysis. To ensure robustness of estimation against the presence of serial correlation and heteroskedasticity in the disturbance term, White period estimates have been used for computing robust standard errors. As a result of an initial estimation, we eliminate the specifications which destabilize the estimation owing to multicollinearity or which do not satisfy either five percent significance or sign condition. We then repeat the estimation and elimination of further variables if necessary, until we obtain stable and significant results.

The results of estimations demonstrate that the estimated coefficients of elapsed week dummy variables show a significant result for almost all commodities, excluding a certain period of time immediately after the launch of products when, by its definition, the estimated value of coefficients is expected to is close to zero. On the whole, the results of estimation in this paper can be said to have shown a quite nice performance.

2.3. Measurement of Pricing Patterns

Next, we measure the average pricing patterns of products by commodities. Since the quality of each product is constant over its life cycle, and changes in macroeconomic conditions are controlled by the time dummy for quarters, changes in the average prices of products with the elapse of time are expressed as changes in the estimated value of coefficients of elapsed week dummy variables. In order to give a picture of pricing pattern of each commodity, we plot the coefficient estimates of week dummies with exponential transformation (exp $(\hat{\gamma})$) along with the elapse of time after the launch of the product. As in Tables 1-1 and 1-2, observation of the patterns reveals that the price of products has a tendency to decrease as time proceeds from the launch for almost all commodities. That is to say, at product turnover, firms appear to set the price of a new product higher than is justified by the quality improvement, which is constant through the life-cycle of the product; they intend to increase the quality-adjusted price to ensure the profitability, whose effect is likely to fall off with the elapse of time.

Moreover, for most commodities, we also observed a tendency that the pace of decrease in product prices becomes moderate as time proceeds. This observation is interpreted to reflect the firms' price setting behavior that, after the initially-set higher price, targeting a small number of price-inelastic consumers, rapidly decreases due to the saturation of demand by those consumers, firms try to appeal to more consumers by gradually decreasing the price.

Observation on the pricing patterns of each commodity reveals that, generally speaking, the quality-adjusted price increase of home electrical appliances is somewhat larger than that of digital consumer electronics, while the pace of price decrease of home electrical appliances also tends to be faster. Such a difference is likely to reflect the perspectives of consumers when they evaluate products. Regarding home electrical appliances, since consumers tend to value more at other elements than quantifiable quality (e.g., design of products and the product image incurred by advertising media), individual products can be differentiated more easily, and the price competition over quantifiable quality tends to be more lenient than digital consumer electronics. As a result, a relatively large increase in quality-adjusted price can be made at the time of launching a new product, and afterwards it falls off substantially as time proceeds.

2.4. Selection of Matched Pairs of Products

In order to verify whether the above-mentioned interpretation of the pricing patterns is reasonable or not, it is useful to understand how much quality-adjusted price increase is made at product turnover. In other words, we would like to characterize the QIR, or how much the quality improvement of a new product accounts for the price difference between new products and old products when launching the former.

When measuring the QIR between new products and old products, it is an important issue how the combinations of new products and old products are selected. If we try to select the pairs of a new product and an old one strictly, we need to accurately understand each manufacturer and the line-up of each product, judge and identify each time which existing line-up the launched new product should be matched to. However, only by using the objective information such as the model names of products and specifications, it is not easy to identify whether a new product belongs to any of the existing line-ups. Moreover, some manufacturers change the product line-up upon the launch of a new product; and therefore, there are many cases in which it is not appropriate in itself to judge, based on the line-up before the launch of a new product, which old product the new one is succeeding to.

Accordingly, in this paper, we place more importance on eliminating the arbitrariness as much as possible in selecting product pairs by defining the matched pairs of products broadly as those satisfying the following selection criteria: (1) The launch (registered) date of a new product is later than that of the old product. (2) New products and old products are made by the same manufacturer. (3) The price of a new product on the launch date is higher than that of the old product on the same day. (4) The quality of the new product is better than that of the old product.[1]

2.5. Measurement of Quality Growth

Based on the matched pairs of new products and old products selected in accordance with the above criteria, we measure the QIR of individual pairs, and examine the shapes of the QIR distributions. The QIR could be defined as follows:

$$\mu_{\tau}^{i,j} \equiv \frac{\sum_k \beta_k \left(X_{j,k} - X_{i,k}\right)}{\ln\left(p_{j,\tau_j+\tau}\right) - \ln\left(p_{i,\tau_j+\tau}\right)} \tag{2}$$

Tables 2-1 and 2-2 express the distributions of the QIR for each commodity by using a kernel density estimation. As the shape of distributions is likely to change with the elapse of time, the distributions are depicted for three points in time: immediately after the launch of a new product (at the 1st week); one month later (at the 5th week); and three months later (at the 13th week).

Looking at the distribution of the QIR, it is a unimodal distribution slightly fat-tailed to the right. Regarding the mode immediately after the launch of a new product, digital consumer electronics have slightly higher values (about 0.6-0.7) than home electrical appliances (about 0.5-0.6). As stated before, this would reflect the difference in the perspectives of consumers when they

[1] Based on these criteria, it is impossible to eliminate pairs of new products and old products which belong to different line-ups (e.g., a pair of "low-end old model" and "high-end new model"). Of course, there is trade-off between securing the objectivity of the selection method and the appropriateness of selection results, either of which should be placed emphasis on a case-by-case basis, if the objectivity of selection method is given importance in selecting the product pairs, there is a concern about possible bias to the analysis results.

In order to eliminate such a concern, we paid attention to the following two additional criteria. The first criterion, *Relative Difference in Quality*, takes advantage of the tendency that the quality difference between a new product and an old one belonging to the same line-up is relatively small. The second criterion, *Levenshtein Distance*, is about the model names of products, which tend to be substantially different for the pair of products belonging to different line-ups. We conducted analysis which excluded the pairs violating each of these two criteria. However, to state the conclusion in advance, the conclusions differ very little regardless of which approach is used, generally confirming the robustness of the analysis results in this paper. For further details, see Abe, Ito, et al. (2016).

evaluate home electrical appliances and digital consumer electronics. Moreover, there is a tendency that the distribution of the QIR gradually shifts to the right and its right tail becomes fatter as time proceeds. This shows that the part of the quality-adjusted price increase fades out with the elapse of time, and this fadeout is accompanied with increased variance of the QIR for a certain period of time.

3. Concluding Remarks

Regarding the price difference between a product and its successor, a classic yet new issue in producing the price index is whether it corresponds to the quality growth of the new product over the old one or to the quality-adjusted price increase as a consequence of the firm's price setting behavior intended to ensure the profitability. It appears to be appropriate to think that in reality the effects of both are reflected in the price difference, but there had been no consensus about their respective degrees of impact has yet to be reached either in practice or in academics.

Under these circumstances, we performed the empirical analysis in this paper using the large-scale data sets of *Kakaku.com*, and measured for each commodity the average tendency in price transition through the life-cycle of durable consumer goods as well as the ratios due to the quality difference out of the price difference between new products and old products.

As a result, it turned out that (i) increases in quality-adjusted price, intended to ensure the profitability when launching a new product; are widely observed; (ii) the pace of price decrease tends to become moderate with the elapse of time; and (iii) home electrical appliances has a somewhat larger degree of quality-adjusted price increase at the launch and a somewhat faster pace of price fall afterwards, compared to digital consumer electronics. Moreover, it was observed that (iv) the QIR, which shows the ratio of the price difference between new products and old products due to the difference in quality, depicts a unimodal distribution fat-tailed slightly to the right, and (v) the mode value of the distribution measured immediately after the launch of a new product indicates about 0.5-0.6 for home electrical appliances, and about 0.6-0.7 for digital consumer electronics.

As far as the authors are aware, there has been little empirical analysis conducted, focusing on the detailed price transitions of individual products as was done in this paper. Therefore, the results of this paper would be useful not only for researchers but also for practitioners of price statistics in that those findings provide empirical support for the so-called 50% rule, which has been proposed or adopted in some countries. Namely, our analysis could justify a quality adjustment method which is easy to adopt even under severe constraints with resources and contributes to improving the precision of the price index.

Currently, the Bank of Japan has announced the rebasing of the PPI by updating the base year from 2010 to 2015. Taking that opportunity, the Bank plans to introduce a new quality adjustment method for some items (eight commodities of household electric equipment and ten commodities of information/communications equipment) based on the thinking of the 50% rule, as a second-best measure for the cases where other quality adjustment methods are difficult to apply. We believe that our analysis could form the basis of the Bank's newly introduced adjustment method in light of empirical adequateness.

4. References

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Ohta, Makoto (1977), A Proposal for Using 50 Percent Rule in Making Quality-Adjusted Price Indexes, *Economic Studies Quarterly*, 28.3, pp.266-269.

Table 1-1: Pricing Patterns over Product Life-Cycle (Home Electrical Appliances)

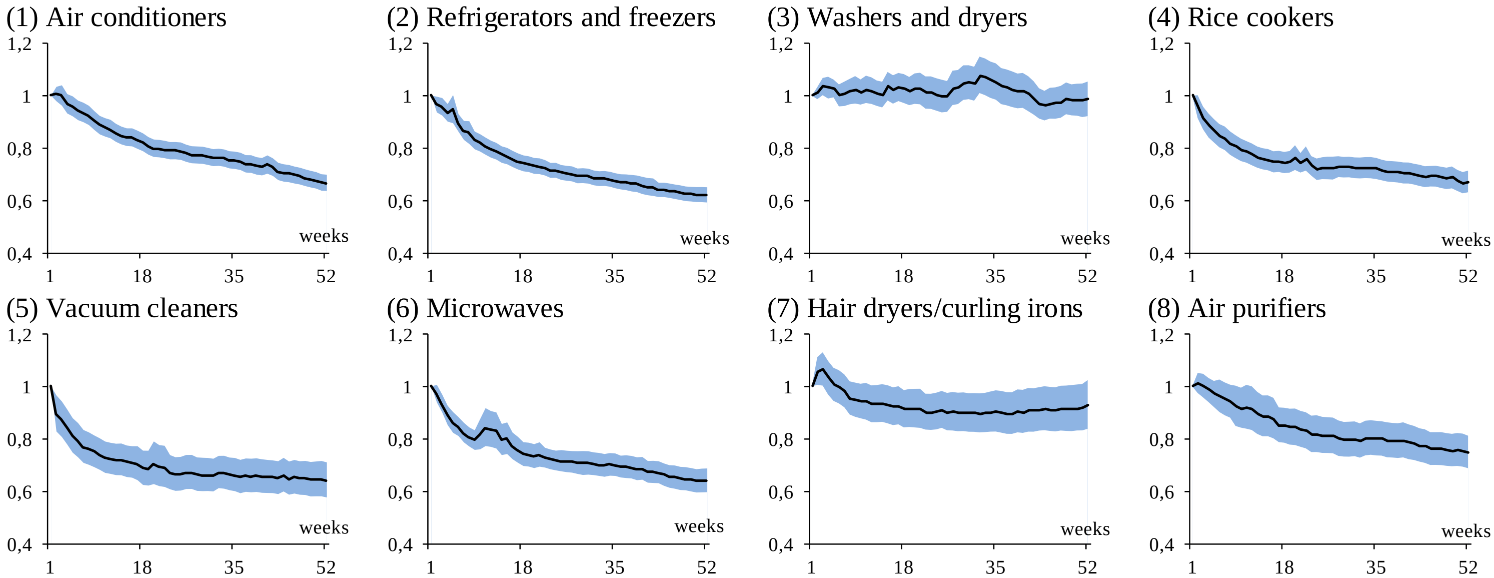
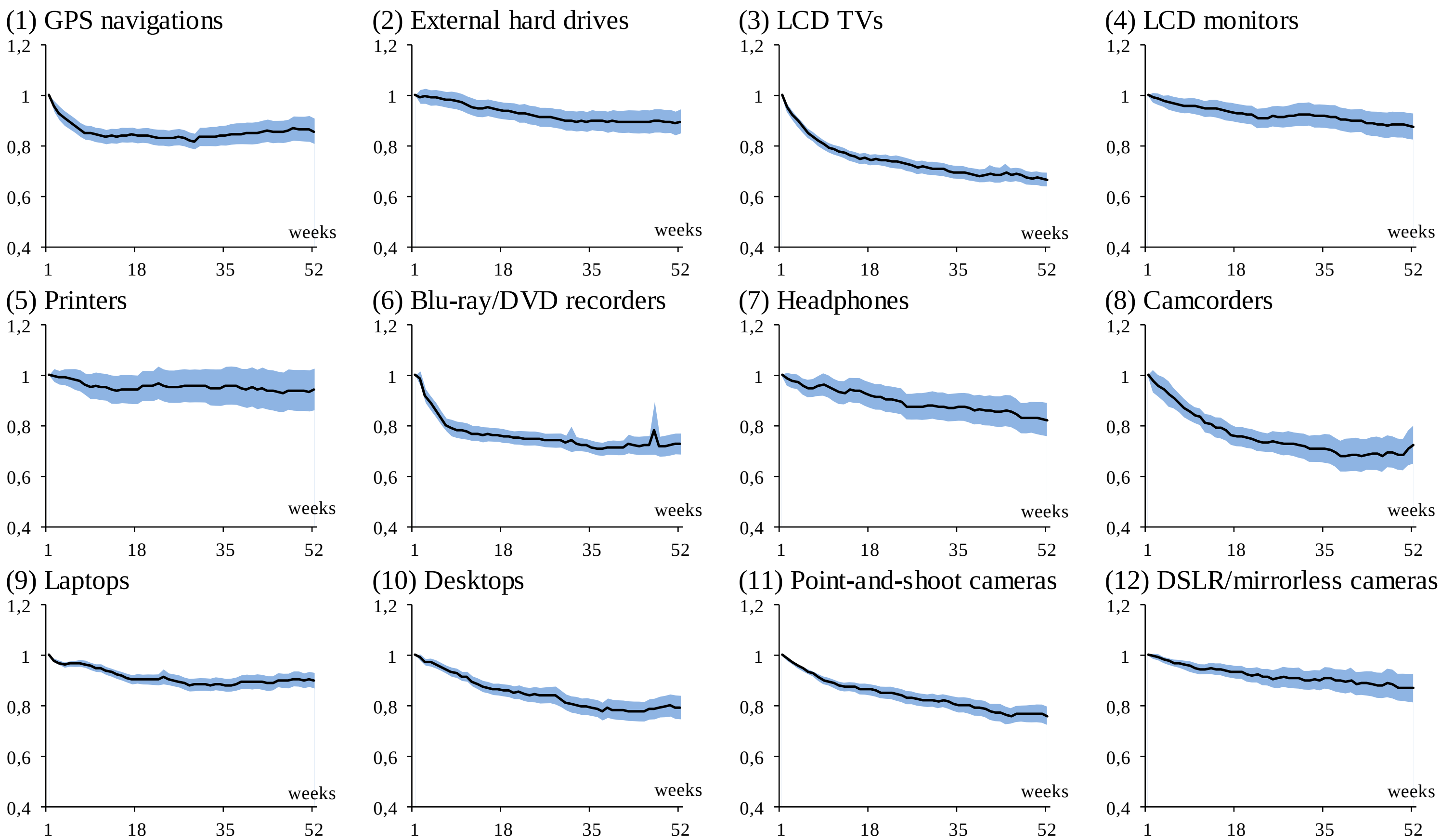


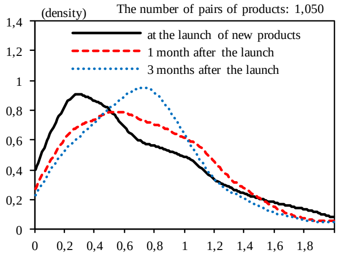
Table 1-2: Pricing Patterns over Product Life-Cycle (Digital Consumer Electronics)



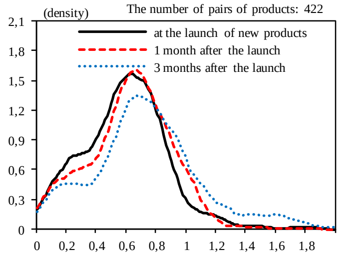
Note: The scale of longitudinal axis is adjusted by dividing a price by the price right after the launch of product. The shaded areas indicate double standard deviation $\pm 2\sigma$.

Table 2-1: Distribution of Quality Improvement Ratios (Home Electrical Appliances)

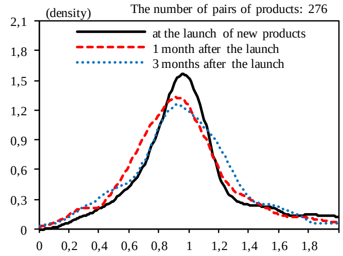
(1) Air conditioners



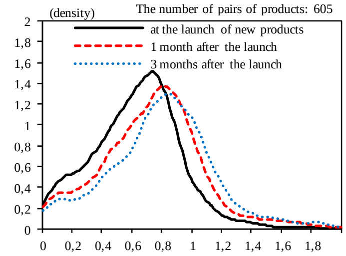
(2) Refrigerators and freezers



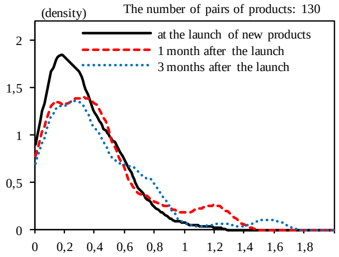
(3) Washers and dryers



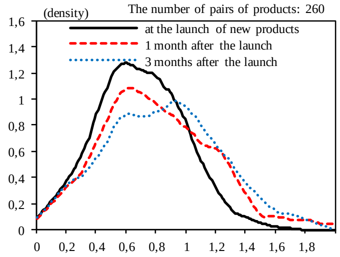
(4) Rice cookers



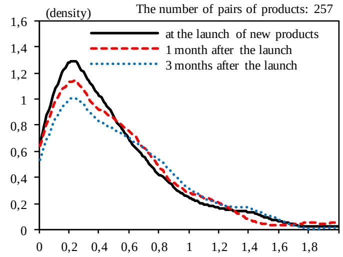
(5) Vacuum cleaners



(6) Microwaves



(7) Hair dryers/curling irons



(8) Air purifiers

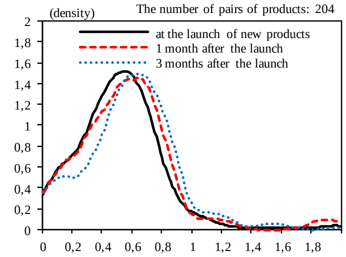
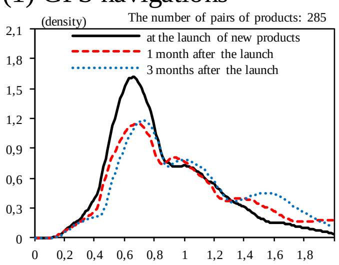
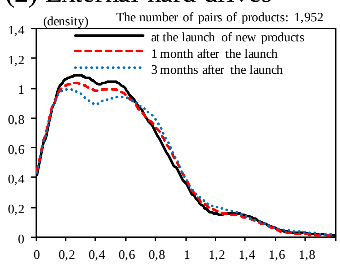


Table 2-2: Distribution of Quality Improvement Ratios (Digital Consumer Electronics)

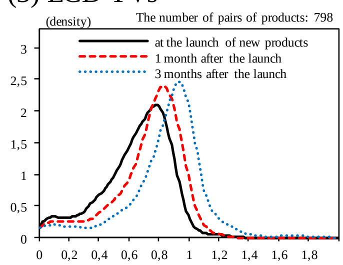
(1) GPS navigations



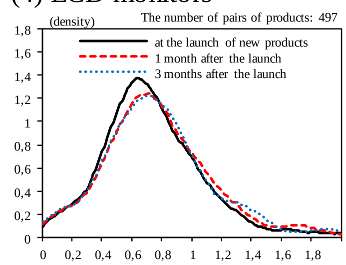
(2) External hard drives



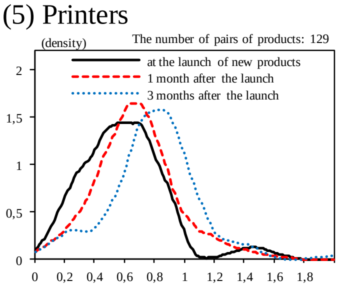
(3) LCD TVs



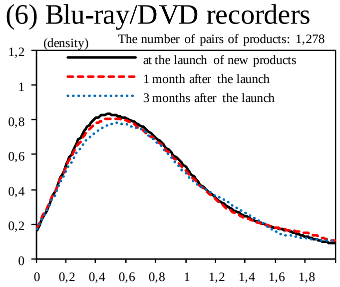
(4) LCD monitors



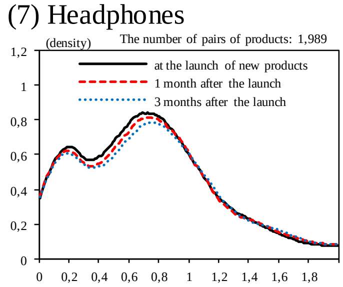
(5) Printers



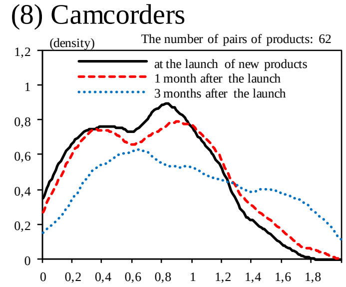
(6) Blu-ray/DVD recorders



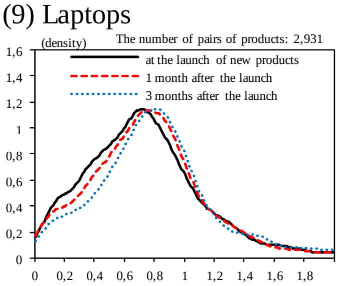
(7) Headphones



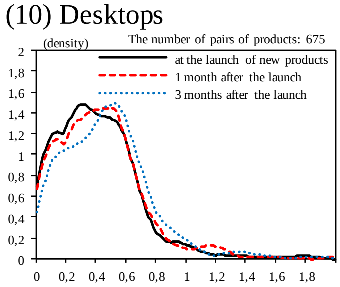
(8) Camcorders



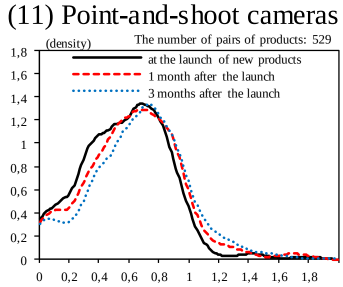
(9) Laptops



(10) Desktops



(11) Point-and-shoot cameras



(12) DSLR/mirrorless cameras