Instability of the Hedonic Model and Its Effect on the Quality Adjustment of Price Indices
– The case of desktop personal computers –*
Preliminary Draft

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Abstract

This paper examines the instability of the hedonic model for desktop personal computers over time and its influence on the quality adjustment of price indices. While previous research has mainly focused on the instability of the hedonic model considering the variety of the functional forms, this paper simulates the quality adjustment using a virtual dataset for price replacements. The results show that the accuracy of quality adjustment depends on the time-lag between the time of model estimation and that of model application to actual price replacements, and that the selection of the functional form should be based not only on the in-sample fit for estimating the hedonic model, but also on the increase in error derived from the time-lag.

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1 Introduction

Quality adjustment by the hedonic method derives the predicted price of new and old products from the hedonic function, which is estimated using observed data at a given point in time, and considers the predicted price ratio as the quality ratio between the old and new products. For a general explanation of the hedonic approach, see Ota (1978) and Shiratsuka (1995). Because the hedonic function may change along with progress in technology, and changes in consumer preferences and market structure, it is highly likely to be unstable over time. Previous research has also empirically demonstrated hedonic function time-series instability.

When implementing quality adjustment using the hedonic method, because the quality adjustment is made using a previously estimated hedonic function to derive the theoretical price, a lag emerges between the time of the estimation and the time of the quality evaluation. If the parameters of the hedonic model become outdated, quality evaluation deviates from the ideal value along with the time lag, influencing quality adjusted price indices.

Accordingly, this paper examines the instability of the hedonic model for desktop personal computers over time and its influence on the quality adjustment of price indices, focusing on how differences in the functional form affect the accuracy of the quality adjustment.

The remainder of this paper is organized as follows. Section 2 provides a brief overview of the previous research. In Section 3 we develop the method of measuring the instability of the function. In Section 4, we present the dataset construction and estimation methods. Section 5 describes the time series behavior of the data. Section 6 presents the estimation results of the hedonic regressions. In Section 7 we discuss how the outdated parameters of the hedonic model cause the quality evaluation deviation. Finally, Chapter 8 presents the conclusions and remarks.

2 Relation with Previous Research

The hedonic function applied for compiling price indices is the regression model of the prices of products on their characteristics. Because the regression model is just a reduced form, it has been noted that when there are changes in technology, consumer preferences, consumer distribution or the market equilibrium conditions, the hedonic function parameters are likely to change.[1]

In empirical studies, Berndt et al.(1995) and Pakes(2003) estimate the hedonic

[1]Many investigations interpret the relational equation between prices and the characteristics generated from a product differentiated market equilibrium as theoretical background to the hedonic function. Related papers include Rosen(1974), Epple(1987), Anderson et al.(1992),Berry et al.(1995, 2004), Feenstra(1995), Petrin(2002), and Ekeland et al.(2004).

function for personal computers, and show that the data reject stability in their PC example. Similarly in Japanese research, Shiratsuka(1995) reports that the estimated hedonic function parameters change over time.

So the instability of the hedonic function has been demonstrated both theoretically and empirically. Yet while previous research examines the performance of the hedonic regressions itself, analyses have not yet been conducted on the extent to which this affects the compiled price indices via quality adjustment.[2] To address this issue, this paper estimates the hedonic function for desktop personal computers in Japan and pursues investigations focusing on the extent of change in the hedonic function over time.

3 Framework for Analysis

3.1 Quality Adjustment Using the Hedonic Method

In the hedonic quality adjustment introduced in Griliches(1961) and elsewhere, quality adjusted prices are derived by assuming that the quality ratio equals the predicted price ratio derived from the hedonic function.[3] In such cases, the quality adjusted price is derived by following formula.

$$Quality\ adjusted\ price = \frac{p_{new}/p_{old}}{\bar{q}} \tag{1}$$

where

$$\bar{q} = \frac{q_{new}}{q_{old}} \tag{2}$$

p list price of the new or old product.

$\bar{q}$ quality ratio between new over old product.

q predicted price of the new or old product calculated by the hedonic function.

Since in many cases hedonic functions are not updated every month, and a time difference arises between model estimation and actual quality adjustment. Consequently, the quality ratio calculated with a hedonic function estimated using old data may deviate from an ideal quality ratio calculated with an ideal hedonic function estimated using the latest data.

[2] Cropper, Deck and McConnel(1988) examine the selection of the functional form. Anglin and Gencay(1996) examine the hedonic function using a semi-parametric estimation, while Moulton(1991) and Gilley and Pace(1995) examine the hedonic function using the Bayes estimator.

[3] This type of quality adjustment by the hedonic method is applied to several items in the Bank of Japan's Corporate Goods Price Index, such as personal computers, servers, printers, video cameras and digital cameras. For additional information about this see, for example, the Bank of Japan's home page. On the other hand, for personal computers in the consumer price index in Japan, a hedonic function covering two consecutive periods is estimated including a time dummy and the price index is compiled from the parameters of the estimated time dummy. See Triplett(2004) for other means of deriving the quality adjusted price using the hedonic method.

3.2 Definition of Instability Measure

In price replacements, the characteristic vectors of the old and new products are $\mathbf{x}_{t-n}$ and $\mathbf{x}_t$, respectively. The old product began to be surveyed at date $t-n$. The price replacement from the old to the new product is conducted at date t. This implies that the new product started to be surveyed at date t and that the quality evaluation is conducted at date t.

$f(\mathbf{x}_t|t-m)$ indicates that a product with the characteristics vector $\mathbf{x}_t$ is valued with the hedonic function estimated at date $t-m$. $f(\mathbf{x}_t|t-m)$ is the hedonic function predicted price of the product with the characteristics vector $\mathbf{x}_t$. Therefore, the quality ratio $g(\%)$ between the old and new products at time t is as follows.[4]

$$g(t,m,n) = \frac{f(\mathbf{x}_t|t-m)}{f(\mathbf{x}_{t-n}|t-m)} * 100 - 100 \tag{3}$$

Then we define the instability measure of the hedonic function as follows.

$$d(t,m,n) = |g(t,m,n) - g^*(t,n)| \tag{4}$$

In eq.(4), $d(t,m,n)$ is defined as the deviation from the ideal quality ratio evaluation, where g^* is calculated by hedonic regression estimated at date t. By this definition, if $m=0$, $g=g^*$. m is the difference between the date of price replacement (quality evaluation by hedonic function) and the date of hedonic function estimation. In eq.(4) when the surveyed price at time $t-m$ is changed to a new surveyed price at date t, $d(t,m,n)$ indicates the deviation from the ideal quality ratio. This deviation is caused by evaluating the quality ratio by the hedonic function estimated at date $t-m$. Thus we can consider this index, $d(t,m,n)$, as the extent of the instability of the hedonic function.

For example, consider the case of $m = 12$ months, $n = 6$ months and $d(t,m,n) = 10$. In this case, the quality adjustment for half-yearly price replacements using the hedonic function estimated 12 months before results in a 10% error in the index. Because the rate of increase in the quality adjusted price is defined as the rate of increase in the list price minus the rate of quality improvement, $d(t,m,n)$ becomes the price index error caused by the outdated parameter.

4 Data and Estimation Methods

In order to analyze the effect from the quality adjustment (the relationship between d and m), we simulate virtual price replacements from the dataset.

Specifically, the following methods are adopted.

[4] As explained below, because the analyses in this paper fix the hedonic function estimation period at 12 months, the starting and ending points of the data used for the function estimation are both determined once time t is given.

Characteristic and price data

- The samples are the release-month prices of products placed on sale between 1999 and 2003, so the price of each product appears in this dataset only once even if it continues to be sold in the market. There are a total of 1,539 samples, and the data is monthly data.
- The data is mostly sourced from *Nikkei PC*(the Japanese personal computer magazine published by Nikkei BP), and includes a few mail-order price samples. Thus the pricing is at the retail level.

Explanatory variables of hedonic function The explanatory variables in estimating the hedonic function are characteristics and time dummies. Specifically, the following characteristics are adopted as explanatory variables.[5]

- CPU clock frequency
- RAM capacity
- Hard Disk Drive (HDD) capacity
- TFT monitor dummy × monitor size
- Time dummy (month of release)

Functional form of hedonic function In this paper, the functional form choice is based on a Box-Cox test to statistically check the goodness of the fit. We estimated the five functional forms, Double Box-Cox, Semi Box-Cox, double-log, semi-log and linear. The linear, semi-log and double-log functional forms can be considered as special cases of the Double Box-Cox or Semi Box-Cox functional forms. The CPU clock frequency and HDD capacity data are transformed into the Box-Cox model.[6] The RAM capacity is not transformed because the log likelihood functions did not successfully converge in the optimization process. The dummies are also not transformed because the variables take non-positive values.

[5] In addition to these variables, there are some important variables in determining the product quality, such as the CPU type, secondary cache capacity, type of optical disk drive, installed software, USB ports and other kinds of interfaces. These characteristics are important to determine the product quality, but these variables are not all available throughout the sample period in our dataset. This is why we do not adopt those variables as explanatory variables. Needless to say, it is possible that such excluded variables may influence the estimation results. In this paper, the problem of omitted variables is considered as a topic for future research.

[6] Because parameters could not be found for optimization of the RAM capacity, the TFT monitor data are not transformed into the Box-Cox model as the monitor value characteristic is zero in products without a TFT monitor.

Sample period Twelve months is adopted as the sample period in estimating each hedonic regression. To capture the time-series changes in the parameters, we conduct a rolling regression with twelve months data.[7]

Product set in changing fo the surveyed prices When the product whose price is surveyed ceases to be representative in the market, the old price is replaced and linked by the new quality adjusted price based on eq.(1). In order to evaluate the hedonic regression method for quality adjustment, we simulate virtual price replacements by setting the representative products at each point. Considering that personal computer model changes frequently take place on a quarterly or semi-annual cycle, we assume a dataset with backward moving averages of prices and characteristics over six months as a representative specification of the product.

5 Characteristics of the Sample Data

The data show that the CPU clock frequency, RAM capacity, HDD capacity and other essential specifications of desktop personal computers consistently rose from 1999 (Table 1, Chart 1).

The average CPU clock frequency, which was 410MHz from February through July 1999, rose by about six times to 2500 MHz from July through December 2003. Over the same time period, the average RAM capacity rose by about five times from around 67 MB to around 355 MB, and the average HDD capacity rose by about 14 times from 9 GB to 131 GB. Additionally, in the monitors sold together with the CPUs as sets, the percentage of TFT monitors rose and the size of the TFT monitors also increased. Overall, the performance of the desktop personal computers rose throughout the sample period.

While the performance increased in this manner, the average product prices declined by about 20 % from an average of around 250,000yen in 1999 to around 200,000yen in 2003.

6 Estimation Results of Hedonic Functions

The results of the hedonic function estimations using the above data for a sample period of 12 months beginning from February 1999 indicate that for almost all periods and functional forms the above-specified explanatory variables are significant overall, but there are some periods when they are not significant and the

[7]Considering rapid technological progress, the function estimation period which is 12 months here should be as brief as possible, with as little old data as possible. Shortening the sample period, however, causes another problem of parameter instability due to the decrease in the number of samples.

sign conditions are not satisfied.[8] Moreover, the estimated function parameters are unstable (Figures 2-5).[9] Especially for the main memory (RAM) capacity, the parameter coefficients are statistically insignificant or show the wrong sign during some periods.[10]

The results of the likelihood ratio tests indicate that while double-log and semi-log Box-Cox are selected for a few periods, Double Box-Cox is selected for almost all of the estimation periods (Tables 2 and 3). The main results of the estimation for each functional form are as follows (Figures 2-5).

- For the linear and semi-log functional forms, the CPU clock frequency, RAM capacity and HDD capacity parameters decline overall. This is because the parameters of those functional forms are dependent on the levels of the explanatory variables.[11]
- For double log functional forms, there are no upward or downward trends in any of the coefficient estimates, reflecting the fact that the coefficients are independent of the levels of the explanatory variables.
- For the Double Box-Cox functional form, the parameter estimates differ by period. Especially, the coefficients of the CPU clock frequency and the Box-Cox transformation parameter have large fluctuations during the period when CPUs with high clock frequencies were released on the market and great growth in the clock frequencies occurred (this period corresponds to the first half of 2001). In addition, the maximum likelihood estimation results show great fluctuations of the transformation parameter λ_i. This indicates that the extent of non-linearity changes in the estimation period.

7 Influence of the Outdated Parameters

In the previous section, we conducted a rolling regression and estimated the parameters of the hedonic regressions. The results indicated that the parameters of

[8] See Tables 6-15 for the detailed parameter values and p-values.

[9] The linear, semi-log and double-log F test results indicate that there are structural changes to the functional forms, and suggest that the functions are unstable.

[10] The influence from the excluded variables is one conceivable reason as to why important characteristic variables that determine the quality, such as the main memory, are found to be insignificant. For example, assume there are two desktop models, A and B, whose variables used in the estimation aside from the main memory all have the same values. Further assume that A has a larger main memory capacity than B, but that in the variables excluded from the estimation B has higher characteristic values. If the price of A is less than the price of B, the estimated value of the main memory parameter could be negative due to the influence from the excluded variables.

[11] As mentioned above, because the hedonic regression is a reduced form, we should exercise caution in the interpretation of each parameter. For the linear and semi-log functional forms, however, the decline in the CPU clock frequency and HDD capacity parameters may reflect the price decline versus the increase in the performance of these parts (frequency, capacity, etc.).

the hedonic regressions depend on the time when the estimation is made. This chapter analyzes the extent to which this hedonic function parameter fluctuation influences the evaluation of the quality ratio between the old and new products on the price replacement.

7.1 d_{mn} differential approach

7.1.1 Analysis method

To confirm the difference in the influence of outdated parameters among the function forms, we begin by comparing the differences in the calculated instability measure d for the different functional forms. Here we define the differences in $d_{mn}(= d(t, m, n))$ between the double Box-Cox, which has the best sample fit, and the other functional forms (linear, semi-log, double-log, and semi Box-Cox) as follows.

$$dd^i_{mn} = d^i_{mn} - d^{dbox}_{mn} \tag{5}$$

where d^i_{mn} stands for the instability caused by the outdated parameter (linear, semi-log, double-log, and Semi Box-Cox), while d^{dbox}_{mn} stands for the instability of the Double Box-Cox function. When $dd^i_{mn} > 0$, the instability of the function i is greater than that in the Double Box-Cox functional form, and when $dd^i_{mn} < 0$, the instability of the function i is less than that in the Double Box-Cox functional form.

Setting Range of M, N In this paper we assume that $6 \le M \le 12, 6 \le N \le 12$ and set 49 pairs $(M, N = 6, \ldots, 12)$. The maximum values for M and N are set at 12 so that the analyses can be conducted with the function re-estimated at least once per year and the surveyed prices changed every 6 months on average.

For example, when compiling the personal computer price index in the Bank of Japan 's Corporate Goods Price Index, the hedonic regression is updated every six months. In accordance with the cycle for new products, price replacements usually emerge every 3-6 months.

$$\begin{aligned} &R^i_{MN} = \Pr(dd^i_{mn} > 0 | M, N) \\ &m = 1, \ldots, M, \\ &n = 1, \ldots, N \end{aligned} \tag{6}$$

Here the price index compilation under the hedonic method (frequency at which the function is updated, average period of price replacements) are characterized by M and N. In compiling the price indices using the hedonic method, by arbitrarily setting the values of M and N in line with the frequency of updating the hedonic function and the average interval between price replacements (product life cycles), we can analyze the extent to which the time-lag between the time of model estimation and that of model application to actual price replacements influences the function instability.

For example, when the hedonic function is updated once per year and the price replacement from the old products to the new products is made every three months on average, d is generated with $M = 12$, $N = 6$, and dd_{mn} is calculated. In this case the calculated $R^i_{12,6} = \Pr(dd^i_{mn} > 0|12,6)$ indicates that the instability derived from the outdated parameter in the function i is greater than that of the Double Box-Cox functional form when the hedonic function is updated once per year and the price replacement from the old products to the new products occurs every three months on average.

Set Range for M and N In this paper we assume that $6 \leq M \leq 12, 6 \leq N \leq 12$ and set 49 pairs $(M, N = 6, \ldots, 12)$. The maximum values for M and N are set at 12 so that the analyses can be conducted with the function re-estimated at least once per year and the surveyed prices changed every 6 months on average.

For example, when compiling the personal computer price index in the Bank of Japan's Corporate Goods Price Index(CGPI), the hedonic regression is updated every six months. In accordance with the cycle for new products, price replacements usually emerge every 3-6 months.

7.1.2 Analysis results

Figures 7 and 8 present the histograms when dd^i_{mn} is generated under the settings $M = 12, N = 12$. Because the histograms show much of the distributions in the positive area, they suggest that the extent of the instability under the linear, semi-log and Semi Box-Cox function forms is greater than under the Double Box-Cox functional form. On the other hand, the double-log histogram shows much of the distribution in the negative area, suggesting that its instability is less than that of the Double Box-Cox.

In order to examine the difference between functional forms in detail, we calculate $R^i_{MN} = \Pr(dd^i_{mn} > 0|M, N)$ from the generated dd^i_{mn}. R^i_{MN} stands for the probability of $dd^i_{mn} > 0$, that is, the probability that the extent of the instability is greater than under the Double Box-Cox functional form. The results are presented as Table 4. The results indicate that while there is not always a statistically significant difference between the extent of the instability of the Double Box-Cox and the other functional forms, R^i_{MN} does indicate the following things.

- For the linear and Semi Box-Cox functional forms, R^i_{MN} generally exceeds 0.5 with some exceptions. Moreover, under these functional forms, R^i_{MN} approaches 0.5 as the value of M increases. These results indicate that the extent of the instability is slightly greater or at least the same as under the Double Box-Cox.

- For the semi-log functional form, all the calculated values of R^i_{MN} exceed 0.5. For this functional form, the value of R^i_{MN} rises along with the value of M. This suggests that in comparison with the other functional forms the extent of the instability in the semi-log functional form increases as the frequency of updating the function declines.

- For the double-log functional form, none of the calculated values of R^i_{MN} exceed 0.5. And the value of R^i_{MN} declines as the value of M rises. This suggests that in comparison with the other functional forms the extent of the instability in the double-log functional form decreases as the frequency of updating the function declines.

In summary, we found that the extent of the influence of the outdated parameters under the Double Box-Cox functional form, which has the best fit, is comparatively smaller than that under the linear, semi-log and Semi Box-Cox functional forms, but greater than that under the double-log functional form.

7.2 Regression Approach

Next the regression approach is applied to investigate the influence of the function updating time on the instability. As in the previous section, upper limits (M, N) are set for the time of updating the function and the intervals of the price replacement (m, n). Then $d_{mn}(m = 1, \ldots, M, n = 1, \ldots, N)$ are calculated under these upper limits and β_{MN} is estimated for each pair of upper limits.

$$\begin{aligned} d_{mn} &= \alpha_{MN} + \beta_{MN} m + \epsilon, \\ &\quad m = 1, \ldots, M, \\ &\quad n = 1, \ldots, N \end{aligned} \tag{7}$$

where α_{MN} and β_{MN} are the estimated parameters and ϵ is an error term.[12] Since we assume that the price replacements are equally distributed by month, β_{MN} represents the relationship between d and m. d indicates the extent of the influence of the updated parameters if the average gap (between the date of estimating the function and the date of the price replacement) is $\frac{M}{2}$ months and the average interval at which the surveyed prices are changed is $\frac{N}{2}$ months. m is the gap

[12] The extent of the instability d may be influenced not only by the time when the function is estimated m but also by the time when the surveyed prices are adopted n. As the analyses in this paper are limited to the time-series changes in the hedonic function, here the conditions are fixed for the time when the surveyed prices are adopted n, in order to analyse on the relationship between m and d.

(between the time of the updating the function and the time of evaluating the quality by hedonic regression) itself.[13]

For example, when the hedonic function is updated once per year and the price replacement from the old products to the new products occurs every three months on average, we estimate eq.(8) with d generated under the settings $M = 12, N = 6$. The estimated parameter $\beta_{12,6}$ indicates the extent of the function instability per month in this case.

7.2.1 Correlation between d_{mn} and m

First we capture the relationship between dmn and m by scatter diagrams. Figure 9 plots the relationship between dmn and m for each functional form. In Figure 9, the horizontal axis shows the gap between the time of estimating the function and the time of the quality evaluation (m) and the vertical axis shows the extent of the function instability epreciation (d_{mn}). The diagrams are plotted with the settings $M = N = 12$ for all the functional forms. The diagrams indicate that there is a positive correlation between d_{mn} and m except under the linear functional form, and they show that the slopes of this positive correlation differ between functional forms. For example, the slope under the semi-log functional form is steeper than that under the other functional forms. In other words, these scatter diagrams indicate that for all the functional forms other than the linear functional form, β_{MN} is positive and its slope may vary by functional form. Next we proceed to estimate β_{MN}.

7.2.2 Estimation Results of β_{MN}

The estimation results, which are presented as Table 5, indicate the following relations among β_{MN}, M, N and the functional forms.

- For all of the functional forms other than linear, the value of β_{MN} increases as N grows larger. That is, the pace of obsolescence becomes faster as the intervals of price replacements grow longer. Therefore, given the pace of quality improvement, the frequency of function updating has a greater influence on price indices as the intervals of the price replacements grow longer. On the other hand, the relationship between the pace of obsolescence β_{MN} and the frequency of function updating M depends on the functional form of the

[13]Here the constant α_{MN} should be 0 based on the definition of dmn, but the estimation results include cases where the t-value is significant. One reason for this may be that while the estimation uses a simple linear function, the actual relation between m and d is not this kind of linear function, but rather a non-linear function. For that reason, to minimize the influence of this non-linearity on β_{MN} when conducting the estimate, this paper sets a maximum limit on the value of M and stipulates the range of values for the explanatory variable m. The estimation results show that the estimated value of β_{MN} changes depending on the value of M, suggesting a non-linear relationship between m and d.

hedonic regression.[14] For the linear functional form, however, the parameter β_{MN} is insignificant. Thus no significant relationship is found between the frequency of updating the function m and the function obsolescence.

- In the influence from the different functional forms, for the semi-log hedonic function the error in the evaluation of the quality ratio increases conspicuously along with the lag in the estimation period. This is because in this functional form the price elasticity of characteristics depends on their characteristic values. Therefore, when there are large increases in characteristic values, the quality improvement from the old to the new products can be over-estimated.[15]

- For the double-log functional form, the error caused by the lag in the estimation period is small. This is because the elasticity of characteristics does not depend on the level of the characteristic values in this functional form. If the function estimation is delayed by a year or more, the quality adjustment error under the double-log functional form is less than that under the Double Box-Cox functional form. Because the Double Box-Cox form has the best in-sample fitting among the functional forms estimated herein, it can also respond flexibly to product sample values that the other functions cannot follow. As a result, it goes too far in fitting outliers, and this apparently lowers its performance for out-of-sample predictions.[16]

Thus, this analysis reaches the same conclusion as the d_{mn} differential approach. That is, when the double-log functiona form is applied for the quality ratio evalu-

[14]For reference, the average monthly rate of change in the "personal computers" item in the Bank of Japan's Corporate Goods Price Index(CGPI) from January 2000 through December 2003 was approximately -3.1%. If, for example, the surveyed price changes indicate that the prices of one-third of the surveyed prices used are marked down (an approach used when the quality of the new products exceeds the quality of the old products), the error from the instability of the function using the Double Box-Cox functional form is approximately 0.2% per month.

[15]This is obvious from the following explanation. For simplification, consider the semi-log hedonic function $\ln P = \alpha + \beta X$ where the characteristic value of the old product is x, the characteristic value of the new product is γx, and γ indicates the rate at which the characteristic value rises. In this case, a linear expression of the quality ratio between the old and new products becomes $\ln P_{new} - \ln P_{old} = \beta x(\gamma - 1)$. This illustrates that the quality ratio between the old and new products depends not only on the hedonic function parameter β and the characteristic value increase ratio γ but also on the level of the characteristic value x itself. For this reason, when the values of β and γ are fixed and the levels of the clock frequency and other characteristic values increase from the old to the new product, the evaluated quality improvement ratio also rises. Under the double-log functional form, however, because $\ln P_{new} - \ln P_{old} = \beta \ln \gamma$, the quality improvement ratio is not dependent on the levels of the characteristic values.

[16]In fact, as may be confirmed from the fluctuation in the Box-Cox transformation parameter, the level of non-linearity of the Double Box-Cox functional form varies greatly depending on the period. Consequently the out-of-sample prediction performance is believed to be lower than that for the double-log functional form (where the Box-Cox transformation parameter is fixed at 0), which has a constant level of non-linearity.

ation, the quality ratio evaluation error caused by the lag of the estimation period is small.

8 Concluding Remarks

As the time-lag between the time of hedonic model estimation and that of application to actual price replacements becomes longer, the evaluation of quality by the hedonic regression method tends to deviate from the ideal value. In particular, when characteristics between the old and new products change greatly, the estimation error increases.

As for the functional form of the hedonic model, although the Double Box-Cox usually fits well in sample, the error may be greater than under a simple double-log functional form when the regression model is updated only once per year, This implies that the selection of functional form should depend not only on the criterion of the sample fit when the hedonic function is estimated but also on the increase in error caused by the time lag from the original estimation to the update. When the improvement in product quality is rapid and the intervals between function re-estimation are extremely long, it is desirable to select double-log and other simple functional forms whose parameters are not dependent on the levels of the characteristic variables.

This paper focuses on the instability of the hedonic regression model over time. Needless to say, when we estimate the hedonic model, we must cope with other problems like missing variables. It should be noted that the performance of the regression model in sample is another issue.

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