Bank of Japan Review 2026-E-11

Expanding and Revising the Application of Hedonic Quality Adjustment in the Corporate Goods Price Index

Research and Statistics Department
FUJII Kentaro*, HIROTA Mihina**, YAMAUCHI Yuriko,
MASUJIMA Ayako, GEMMA Yasufumi

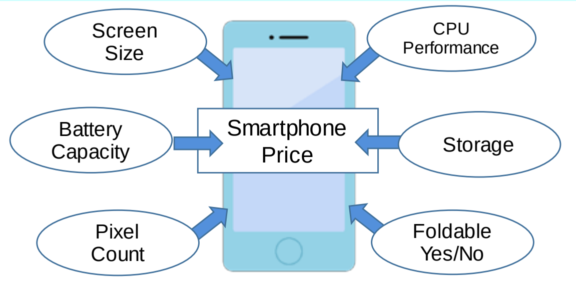
August 2026

The Corporate Goods Price Index (CGPI) employs the hedonic method for quality adjustment. This statistical method estimates the relationship between product quality and prices in an objective manner. Its strength lies in its ability to accommodate a wide range of quality variations, and it is currently applied to five items, including passenger cars. In conjunction with the process for the rebasing of the CGPI to the 2025 base year, we are considering expanding the range of products quality-adjusted using the hedonic method and modifying the hedonic quality adjustment method for certain products as follows: (i) newly applying a time-dummy hedonic method to microprocessors (MPUs) to appropriately capture price trends amidst rapid product cycles; (ii) applying to passenger cars a hedonic method that accounts for quality differences in advanced autonomous driving technology; and (iii) applying separate hedonic models to interchangeable-lens camera bodies and lenses in order to evaluate lens performance differences in more detail. These initiatives are expected to improve the accuracy of quality adjustment in the CGPI.

Introduction

The Corporate Goods Price Index (CGPI), compiled and published by the Bank of Japan, aims to continuously capture price changes for goods that are traded at constant trade conditions with unchanging quality. In practice, however, due to shifts in demand structure and technological innovation, the goods on the market change over time. As a result, it is not always possible to continue surveying the same products, and surveyed products often need to be replaced over time. In such cases, the price difference between old and new products must first be identified, after which the "price difference resulting from quality changes" is removed so that only the "pure price change" is reflected. This process is referred to as "*quality adjustment*." Several methods for quality adjustment are available depending on product characteristics and data availability. [1] Among these methods, the hedonic method is particularly useful when price differences reflect differences in quality, as measured by characteristics such as function and performance. Under the hedonic method, the "price difference resulting from quality change" is estimated using a regression equation (hedonic model) that represents the relationship between product characteristics and prices (Chart 1). Currently, the CGPI applies hedonic quality adjustment to five items, including smartphones and passenger cars. Because the hedonic method analyzes the relationship between product characteristics and prices using a large amount of data, it enables an objective evaluation of the relationship between quality and price based on statistical methods and data rather than analysts' subjective judgment. In addition, even when multiple function and performance characteristics change simultaneously, the method can comprehensively evaluate the contribution of each characteristic to price. For these reasons, the hedonic method has been widely used not only in Japan but also in many countries and across a broad range of products in the compilation of price indices (Chart 2).

[Chart 1] Concept of Quality Adjustment Using the Hedonic Method



1. Analyze the relationship between product characteristics and prices using large amounts of data
2. Estimate relationships such as "one additional CPU core → a 2% increase in price"
3. For constant-quality comparison, adjust the price of a new model with one more CPU core downward by 2% before comparing it with the old model

[Chart 2] Products Subject to the Hedonic Method in Price Indices in Major Countries

United States	Microprocessors*, Internet access service**, Desktop computers*, Laptop computers*, Servers*, Televisions, Other video equipment, Washers and dryers, Refrigerators and freezers, Microwave ovens, Ranges and cooktops, Clothing etc., Phones,accesories and smartwatches, Photographic equipment, land-line telephone services, Cable and satellite television service, Watches, Wireless phone service
United Kingdom	PCs, Laptop computers, Tablet computers, Smartphones, Smartwatches
Germany	Desktop PCs**, Notebooks**,Tablet PCs**, Servers*, Printers**, Processors*, RAM*, Hard drives (HDD**,SSD*), Smartphones**, Used cars, Residential real estate
France	Laptop computers, Smartphones, Televisions, Dishwashers, Washing machines, Refrigerators, Books
Canada	New housing*, Computer equipment, Software and supplies, Internet access services, Rent, Used cars, Cellular services from telecommunication service retailers

Note1: As of September 2025.
Note2: Unmarked items are Consumer Price Index (CPI) items; * denotes Producer Price Index (PPI) items; ** indicates items for which the hedonic method is used in both the CPI and the PPI.

To ensure that the relationship between product characteristics and prices reflects current market conditions, the CGPI re-estimates hedonic models once or twice a year using the latest available data. In addition, at the time of rebasing the CGPI to the new base year (conducted every five years), the accuracy of quality adjustment has been maintained and improved by expanding the range of products subject to the hedonic quality adjustment method and reviewing the hedonic models. As part of the ongoing procedure for the rebasing the CGPI to the 2025 base year, the Bank of Japan is considering the following: (i) newly introducing the hedonic method for microprocessors (Micro-Processor Units: MPUs); (ii) improving the hedonic model for passenger cars; and (iii) estimating separate hedonic models to interchangeable-lens camera bodies and lenses. This paper describes the background to these considerations, proposes new methodologies, and presents the estimation results.

Introduction of the Hedonic Method for MPUs

Background

An MPU is a semiconductor chip that integrates the functions of a central processing unit (CPU), the core component of a computer. In the CGPI, MPUs are surveyed under the Import Price Index (IPI) item "MOS logic integrated circuits."

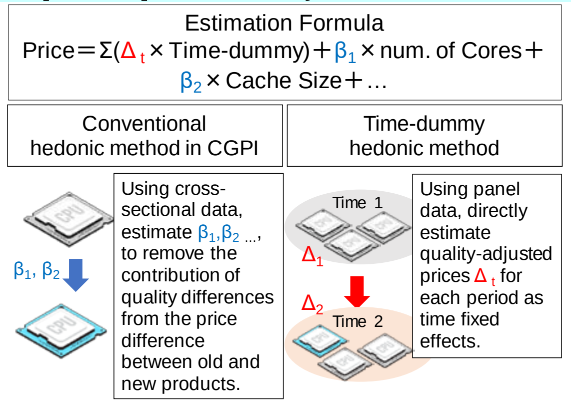
MPU performance improves rapidly over time under the so-called "Moore's Law," where product turnover is frequent and the price of older products decline quickly. Therefore, price index compilation requires timely replacement of representative products and accurate measurement of the relationship between quality improvements and price changes.

Currently, MPU quality adjustment at the time of product replacement relies on the "production cost method," which regards the production costs required for quality improvements as the "price difference resulting from quality changes." In practice, however, it is often difficult to obtain cost information on quality differences between old and new products from reporting companies, making appropriate quality adjustment challenging. In addition, from the perspective of reducing survey burden, surveyed products are selected based on whether they are expected to remain representative and continuously traded. As a result, the survey may not fully keep up with the frequent product turnover observed in the MPU market. If the latest products are not included in the survey, there is concern that overall industry price trends may not be adequately captured.

To better capture industry-wide price trends, we examine the estimation of quality-adjusted prices using the "time-dummy hedonic method," following the approach adopted by the U.S. Bureau of Labor Statistics (BLS) in compiling MPU price indices in the United States.

The conventional hedonic method in the CGPI uses cross-sectional data to estimate the relationship between quality differences and price differences. Then, each time a surveyed product is replaced, the characteristics of the old and new products are substituted into the hedonic model to estimate the "price difference resulting from quality changes." In contrast, the time-dummy hedonic method examined in this paper directly estimates pure price changes, unlike the conventional hedonic method (Chart 3). In the time-dummy hedonic method, quality-adjusted price changes—that is, pure price changes—are estimated as time fixed effects (the coefficients of time-dummy variables) in a panel data analysis framework, and are directly reflected in the price index.[2] This method makes it possible to estimate market-wide trends in quality-adjusted prices without being influenced by the price changes of individual products, particularly in the MPU market where product turnover is rapid. The CGPI is adopting the time-dummy hedonic method for the first time.

[Chart 3] Time-dummy Hedonic Method



Note: In this paper, the functional form is specified with adjustments such as logarithmic transformation of prices. Under a two-period rolling estimation framework, the coefficients of the time-dummy variables correspond to price change rates.

Estimation Method

The hedonic models to be estimated are as follows. As MPU prices are highly influenced by global semiconductor supply and demand conditions, we assume that over the long term, import prices and domestic retail prices are considered to exhibit similar trends; therefore, the estimation in this study is based on domestic retail prices, although the CGPI surveys import prices for MPUs. The explanatory variables include time-dummy variables representing the timing of prices, as well as key MPU characteristics such as the number of cores, thermal design power (TDP), base and maximum clock frequencies, number of threads, and cache size.[3] The estimation dataset is constructed from MPU price and specification (spec) information collected from online shopping websites and related sources. The dataset includes only products released within two years prior to the estimation period, taking into account product release cycles and representativeness.

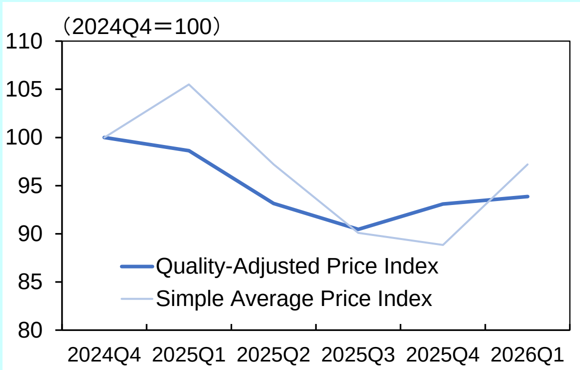
Following the approach adopted by the BLS, this study employs a "rolling" estimation method. This method repeatedly estimates the coefficients of time-dummy variables using panel data over rolling periods. The MPU market is characterized by rapid technological progress, and both the evaluation of product characteristics and the product mix can change significantly over short periods of time. In such a market, rolling estimation makes it possible to capture market-wide changes associated with the introduction of new products, while reducing biases caused by obsolete products remaining in the dataset.[4] In addition, this approach has a practical advantage. By restricting the estimation period to a fixed moving window, it reduces large revisions to past indices when new observations are added. Specifically, the coefficients of the time-dummy variables are repeatedly estimated each quarter using panel data for the most recent two quarters. Quarterly price changes implied by these coefficients are then chained together to construct the price index. Furthermore, to account for differences in supply and demand by usage, MPUs for personal computers (PCs) and servers are estimated separately. The sample size for each estimation was approximately 50 products for both PCs and servers.

Estimation Results

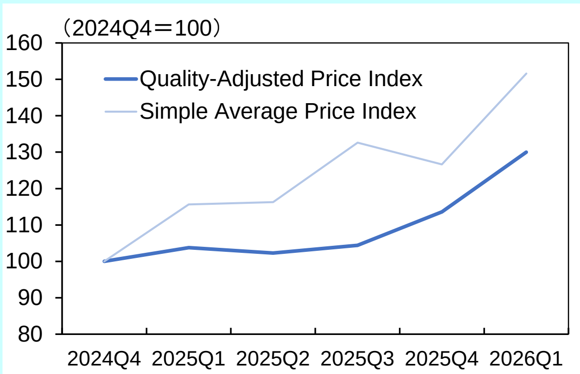
Chart 4 presents the quality-adjusted MPU price indices estimated using the time-dummy hedonic method for the six quarters from the fourth quarter of 2024 through the first quarter of 2026. While the index of MPUs for PCs followed a downward trend until around mid-2025, the index for servers exhibited an upward trend. This suggests that increased investment in data-center servers pushed MPU prices upward, even after accounting for quality improvements such as enhanced AI-processing capabilities during this period.

[Chart 4] Preliminary estimates of MPU Price Index

for PCs



for Servers



Compared with the simple average price index in the dataset—in other words, this can be described as the price without quality adjustment—the quality-adjusted price index exhibits more moderate fluctuations after removing the effects of quality changes.

However, because the index changes can currently be observed for only five quarters, further data collection is necessary to assess the validity and robustness of the observed trends.

As with the BLS, this estimated index could be directly used as the CGPI price index for MPUs. However, Japan's economic structure differs from that of the United States because Japan relies heavily on imported MPUs. Therefore, a price index estimated solely from domestic retail price data may not adequately reflect import price specific factors, such as changes in import pricing associated with tariffs, or transfer-pricing adjustments within corporate groups. These factors may be absorbed into retail margins before reaching the retail price level, making it difficult to fully capture import price changes. Taking these factors into account, the primary source data for the CGPI will continue to be prices reported by companies under the existing survey framework. The price trends estimated using the time-dummy hedonic method will be used to supplement survey data by reflecting market price trends that may not be fully captured through surveys by reporting companies.

Revision of the Hedonic Model for Passenger Cars

Background

For passenger cars, the CGPI surveys domestic transaction prices, export prices, and import prices. Since the automobile industry is one of Japan's key industries, it is particularly important to accurately compile price indices for passenger cars. However, quality adjustment for passenger cars is challenging because of the wide variety of product characteristics. To address this issue, the CGPI has applied hedonic quality adjustment for passenger cars since the 2015 base-year index. Furthermore, since the 2020 base-year index, it has also used machine-learning techniques to automatically select variables for the hedonic model. This has substantially expanded the range of functions and performance characteristics incorporated into quality adjustment.[5]

In recent years, the automobile industry has experienced significant advances in autonomous driving technologies. Autonomous driving refers to technologies that enable vehicles to perform driving tasks without driver intervention. Depending on the degree of automation, autonomous driving is classified into five levels, ranging from Level 1, which provides driver assistance only, to Level 5, in which all driving tasks are fully automated (Chart 5). Until recently, Advanced Driver-Assistance Systems (ADAS), classified as Level 1 technology, have been the mainstream, and existing hedonic models have included them as explanatory variables. More recently, vehicles equipped with Level 2 functions—often described as advanced driver assistance or partial automation—have become increasingly widespread. As a result, the adoption of autonomous driving technologies has significantly improved vehicle quality.

[Chart 5] Level of Autonomous Driving

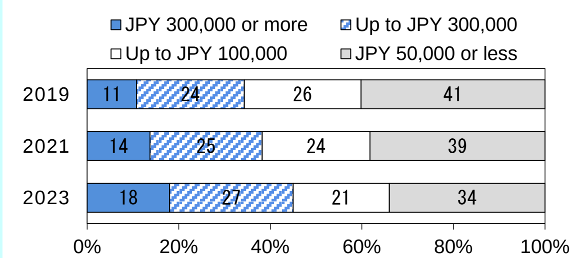
Advanced technology

Level		Description
5	Full Driving Automation	Can drive the vehicle under all conditions
4	High Driving Automation	Can drive the vehicle under limited conditions without driver intervention
3	Conditional Driving Automation	Can drive the vehicle under limited conditions, but driver intervention may be required
2+	Partial Driving Automation	Example: Hands-free driving on highways (automated lane changes, merging and exiting)
2	Partial Driving Automation	Provide steering AND brake/acceleration support to the driver Example: Adaptive cruise control with lane keeping (combination of level 1)
1	Driver Assistance	Provide steering OR brake/acceleration support to the driver Example: Automatic emergency braking, cruise control, and lane keeping assist

Source: Society of Automotive Engineers of Japan (JSAE), Ministry of Economy, Trade and Industry, and Ministry of Land, Infrastructure Transport and Tourism

As autonomous driving technologies become more advanced, the number of electronic components, such as cameras and radar systems, increases. This raises production costs and affects passenger car prices. In addition, consumers' willingness to pay for ADAS and autonomous driving functions has increased over time (Chart 6). Therefore, to compile a constant-quality price index for passenger cars, it is necessary to appropriately remove price changes attributable to advances in autonomous driving technologies.

[Chart 6] Consumers' willingness to pay for ADAS and autonomous driving functions

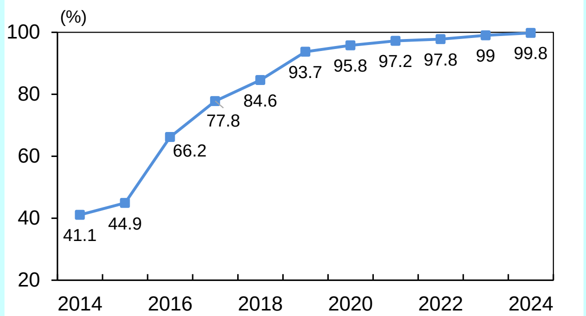


Source: Japan Automobile Manufacturers Association

Another issue is that some of the functions currently incorporated into the hedonic model have already become widely standardized. For example, safety features such as Advanced Emergency Braking

Systems (AEBS), which have become standard equipment as a result of regulatory requirements, are now installed in most vehicle models. Consequently, the effectiveness of these functions as explanatory variables has declined (Chart 7).[6] Therefore, the model needs to be updated to reflect more advanced ADAS and autonomous driving technologies rather than functions that have already become widespread.

[Chart 7] AEBS installation Rate



Source: Japan Automobile Manufacturers Association

Examination of Additional Variables

In considering additional variables for the hedonic model, advanced ADAS and autonomous driving technologies offered by different manufacturers under various names were reviewed and compared. Functions which are likely to become more widespread were selected for inclusion. Specifically, the 40 best-selling vehicle models sold in Japan, including imported vehicles, were classified into four price segments: high (approximately 8 million yen or more), upper-middle (approximately 4.5 million to 8 million yen), lower-middle (approximately 2.5 million to 4.5 million yen), and low (approximately 2.5 million yen or less). Since new technologies tend to be introduced first in higher-priced vehicles, we focused on functions that were more common in the upper price segments. As a result, the following four variables were added to the dataset.

(1) Cruise control with stop-and-go:

A function that keeps the vehicle stopped even after the driver releases the brake pedal and automatically resumes following the preceding vehicle when it starts moving again. This is a type of adaptive cruise control that operates at all speeds. Although classified as a Level 1 driving-assistance technology, its adoption rate has increased significantly in recent years.

(2) Cruise control with lane-keeping assist:

A function that automatically accelerates and decelerates in response to the preceding vehicle while assisting with steering control to reduce driver workload. This is classified as a Level 2 driving-automation technology.

(3) Driver monitoring system with emergency assist:

When the system determines that the driver is unable to continue driving safely, it automatically slows and stops the vehicle while assisting with steering control. This function is classified as a Level 2 driving-automation technology.

(4) Hands-free driving assistance:

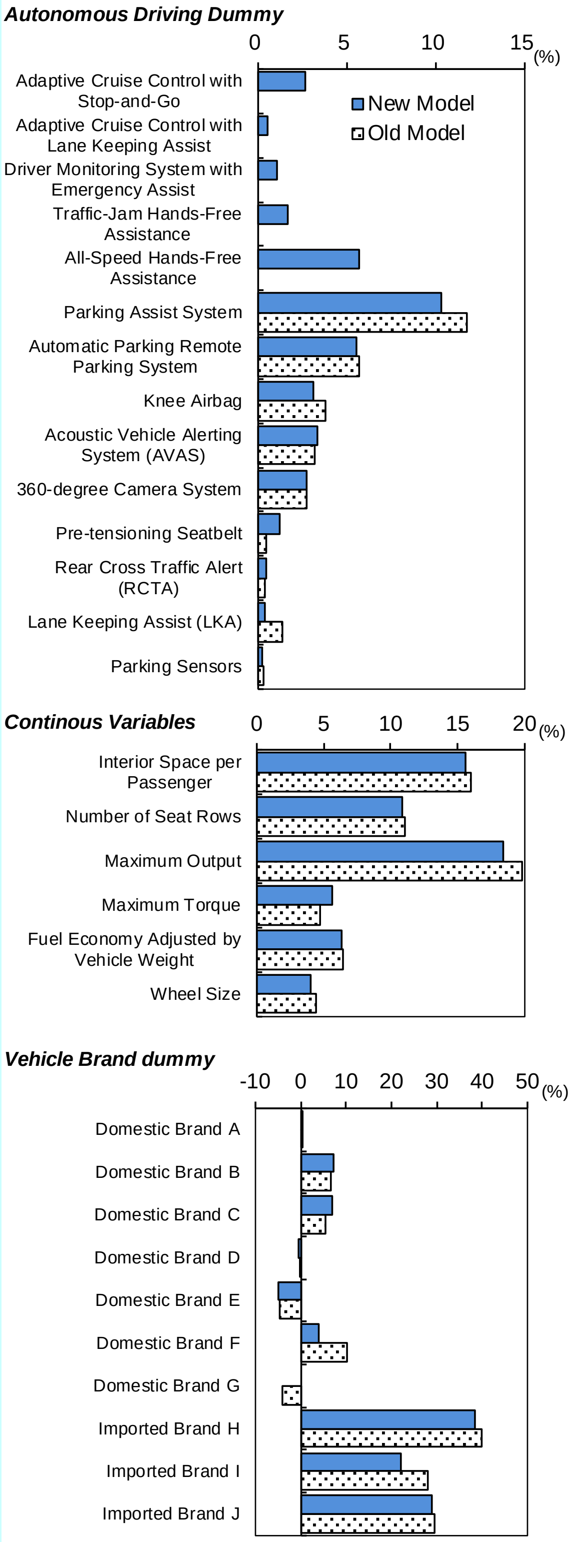
A function that allows the driver to remove their hands from the steering wheel in limited situations, such as highway driving. This function is classified as Level 2+ driving-automation technology.[7] Although this technology is currently limited mainly to mid-to-high-end vehicle models, wider adoption is expected in the future. The model distinguishes between "traffic-jam hands-free assistance," which permits hands-off driving only at low speeds, mainly during traffic congestion, and "all-speed hands-free assistance," which allows hands-off driving across a broader speed range, including highway speeds.

The hedonic model estimation uses a dataset containing performance information and manufacturer recommended retail prices for both domestic and imported passenger cars.[8] As with the existing hedonic quality adjustment framework, the analysis is based on catalog data from Goo-net, a used-car information website operated by the Japanese automobile-related information platform company Proto Corp. Based on vehicle specification and equipment tables, we added dummy variables indicating whether each of the functions described in (1)-(4) was installed to the dataset. We then estimated the hedonic model using the expanded dataset. Consistent with the existing estimation framework, the hedonic model was estimated using the Adaptive Elastic Net (AEN), which simultaneously performs variable selection and coefficient estimation to automatically construct stable models with good statistical fit.

Estimation Results

The estimation results are presented in Chart 8. All four of the newly added variables were selected in the hedonic model, indicating that the model is capable of capturing quality differences associated with whether advanced autonomous driving technologies are installed. In addition, the contribution of brand dummy variables and other explanatory variables declined after these variables were added. This suggests that the effects of autonomous driving technologies on prices can now be captured more directly, rather than through brand effects or other explanatory variables.

[Chart 8] Estimated Contributions of Individual Characteristics to Price



Note: The contribution of each variable is defined as the percentage impact on price when that variable increases by one standard deviation for continuous variables or by one unit for dummy variables, holding all other characteristics at their mean values.

However, the four newly added functions are still limited to a relatively small number of higher-end vehicle models. In addition, because the estimation period since 2025 is still short, only a few model replacements involve changes in these functions. For now, the analysis is limited to evaluating the estimation results. We have not yet compared the price indices produced by previous and revised models. Additional validation will be needed as more data becomes available.

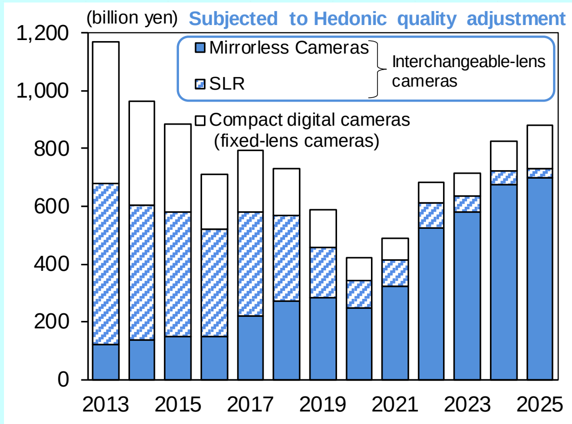
To the best of the authors' knowledge, no other country has yet applied hedonic quality adjustment to new passenger cars. The CGPI therefore represents a pioneering application of this method.[9] Building on this existing framework, the present study incorporates more advanced autonomous driving features as explanatory variables to enhance the hedonic model. This is expected to improve the accuracy of price statistics.

Separation of Hedonic Models for Camera Bodies and Lenses in Interchangeable-Lens Cameras

Background

For interchangeable-lens cameras, including mirrorless cameras and single-lens reflex (SLR) cameras, the CGPI surveys domestic transaction prices, export prices, and import prices. Although the interchangeable-lens camera market temporarily contracted because of the spread of smartphones and the COVID-19 pandemic, it has recently expanded, particularly in the mirrorless camera segment. Manufacturers have increasingly focused on image quality and other features that differentiate these products from smartphones (Chart 9).

[Chart 9] Digital Camera Market Size



Source: Camera & Imaging Products Association

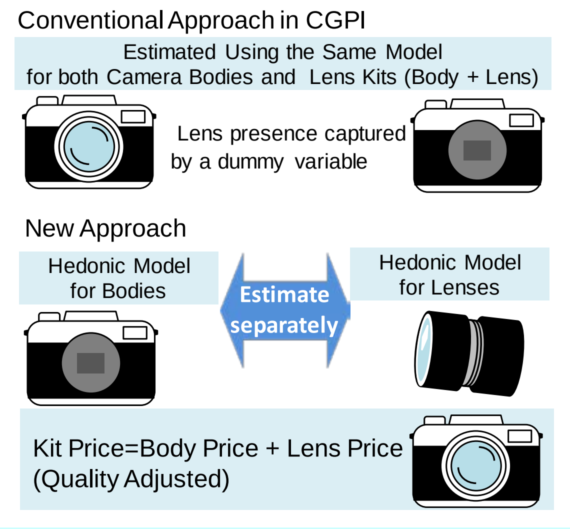
Currently, when applying the hedonic method to interchangeable-lens cameras, both camera bodies and bundled products consisting of a camera body and interchangeable lens (lens kits) are estimated using a single hedonic model. In this framework, the price effect of the lens is estimated using both variables representing lens performance and a dummy variable indicating whether the product is sold as a lens kit. However, estimation based on a single equation tends to be dominated by the prices of camera bodies, which are generally much higher than those of lenses, making it difficult to adequately identify the contribution of lens performance to prices. In addition, although a lens-kit dummy variable is included in the model, a single hedonic model cannot fully separate the effects of camera bodies and lenses. As a result, it is difficult to adequately capture quality differences associated with individual lens characteristics.

New Method

This study examines a method that separately estimates camera bodies and lenses, whose price levels and quality-characteristic structures differ substantially. This method thereby avoids estimation biases that can arise when they are treated within a single hedonic model. By estimating separate hedonic models for camera bodies and lenses, the contribution of lens performance to prices can be identified independently of camera body prices. This approach is expected to improve both the accuracy of quality adjustment and the interpretation of the estimation results. For lens kits, we substitute the characteristics of the camera body and lens into the separately estimated hedonic models and treat the resulting values as the theoretical prices of each component. We then sum these theoretical prices to derive the theoretical price of the lens kit and measure quality differences between old and new products by comparing changes in the combined theoretical prices (Chart 10).[10]

The dataset for estimating the hedonic model for camera bodies was constructed in the same manner as that used in the conventional hedonic quality adjustment procedure in the CGPI. Price and performance information for mirrorless and SLR camera bodies were collected from online shopping websites and other relevant sources. To account for product release cycles and market representativeness, the sample was limited to products released within the previous seven years, resulting in a dataset of 100 products. For the lens model, price and performance information for interchangeable lenses was collected using the same approach. Given the shorter product cycles of newly released lenses, the sample was limited to products released within the previous two years, resulting in a dataset of 265 products. As with passenger cars, the hedonic models were estimated using the AEN.

[Chart 10] Separating Hedonic Models for Interchangeable-Lens Cameras

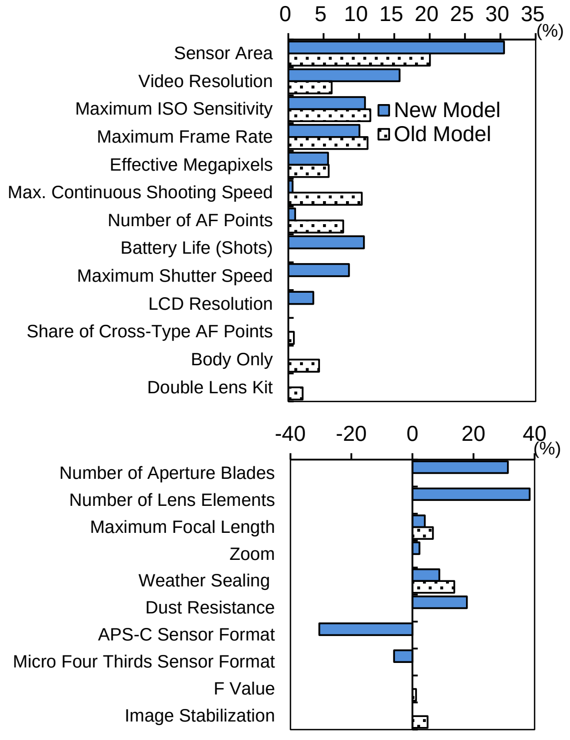


Estimation Results

Chart 11 compares the relationship between product characteristics and price based on a single hedonic model that does not distinguish between cameras and lenses (old model) with the results estimating separate hedonic models for each (new model). For camera bodies, no substantial differences were observed in the main explanatory variables between the old and new models. In contrast, for interchangeable lenses, the number of explanatory variables increased, particularly among continuous variables such as the number of lens elements and the number of aperture blades, both of which directly affect image quality. As a result, quality differences associated with lens performance were captured more clearly. These findings suggest that estimating camera bodies and lenses separately makes it possible to better reflect lens-specific quality characteristics independently of camera body prices. This approach is therefore expected to improve the accuracy of quality adjustment for lens kits.

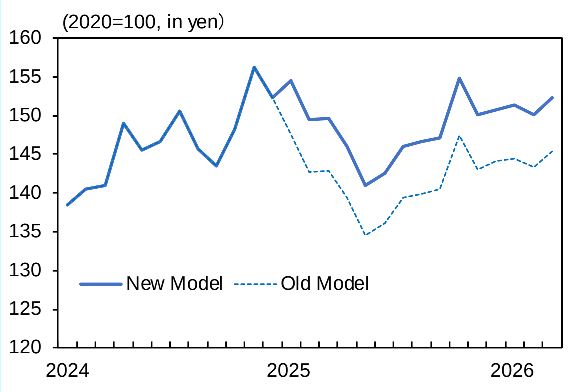
Chart 12 presents the results of applying the revised estimation framework to the item "Video equipment and digital camera" in the expert price index. As additional explanatory variables related to lens performance were incorporated, the index based on the new model showed somewhat higher movements than the index based on the old model. This suggests that product quality characteristics are now being captured more appropriately than before, leading to a better reflection of price differences across products.

[Chart 11] Estimated Contributions of Individual Characteristics to Price



Note: The contribution of each variable is defined as the percentage impact on price when that variable increases by one standard deviation for continuous variables or by one unit for dummy variables, holding all other characteristics at their mean values. In the old model, camera body and lens contributions are shown separately but are derived from the same model. In the new model, they are estimated separately. Therefore, the contribution rates are not directly comparable.

[Chart 12] Index Changes under the Old and New Models (Trial Estimates)



Concluding Remarks

In the process of the rebasing the CGPI to the 2025 base-year index, the Bank of Japan plans to further enhance the accuracy of quality adjustment through both expansion of the range of products subject to the hedonic quality adjustment method and improvements in the methods applied to existing products. The validity of the new initiatives described in this paper will need to be assessed further as additional data become available before the release of the 2025 base-year index. Looking ahead, we will continue to improve the accuracy of the CGPI and expand the range of applications for the hedonic method.

* Currently at the Hakodate Branch
** Currently at the Sendai Branch

[1] For details of CGPI quality adjustment, see Chapter 7 of the Explanation of the CGPI (2020 base; available in Japanese only).

[2] During the late 2000s and 2010s, concerns emerged whether microprocessor price indices were adequately reflecting market conditions. In response, BLS replaced the matched-model approach to the time-dummy hedonic method. For details, see: Sawyer, S. D., and A. So. 2018. "A New Approach for Quality-Adjusting PPI Microprocessors," Monthly Labor Review, U.S. Bureau of Labor Statistics.

[3] Consistent with the BLS approach, this study incorporates PassMark scores to capture characteristics that cannot be fully explained by major product characteristics.

[4] A single time-dummy hedonic estimation over the entire sample period tends to be strongly influenced by quality structures observed in the past.

[5] Since the 2020 base-year CGPI, the Adaptive Elastic Net (AEN), a sparse estimation method that simultaneously performs variable selection and coefficient estimation to construct stable models with good statistical fit, was introduced. For further details regarding the AEN, see: Furuta, S., Y. Hatayama, A. Kawakami, and Y. Oh. 2020. "New Hedonic Quality Adjustment Method using Sparse Estimation," Bank of Japan Working Paper Series, No. 21-E-8.

[6] In Japan, these safety features became mandatory for new domestic vehicle models in November 2021 and new imported vehicle models in July 2024. The requirement was extended to continuously produced models in December 2025.

[7] Because drivers must continuously monitor the driving environment and intervene, when necessary, these functions are not classified as Level 3 autonomous driving technologies.

[8] The dataset contains approximately 20 continuous variables and 100 dummy variables, covering performance-related features, vehicle type, brand, and product release timing.

[9] Used-car quality adjustment often relies on stable indicators such as vehicle age and mileage and is applied in Germany and Canada. In contrast, new passenger cars continuously incorporate new technologies such as advanced safety functions, requiring ongoing updates to both the dataset and the hedonic model, and making quality adjustment more complex.

[10] The lens model can also be applied to the PPI and EPI item "Exchange lenses for cameras," which is expected to result in improved accuracy of the hedonic quality adjustment for the price index for standalone lenses.

The Bank of Japan Review Series is published by the Bank to explain recent economic and financial topics for a wide range of readers. This report, 2026-E-11, is a translation of the Japanese original, 2026-J-8, published in June 2026. Views expressed are those of the authors and do not necessarily reflect those of the Bank.

If you have any comments or questions, please contact Research and Statistics Department (E-mail: post.rsd3@boj.or.jp). The Bank of Japan Review Series and the Bank of Japan Working Paper Series are available at https://www.boj.or.jp/en/index.htm.