Product Turnover and the Cost of Living Index

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Abstract

This paper evaluates the effects of product turnover on a welfare-based cost-of-living index. We first present some facts about price and quantity changes over the product cycle employing scanner data for Japan for the years 1988-2013, which cover the deflationary period that started in the mid 1990s. We then develop new methodology to decompose price changes at the time of product turnover into those due to the quality effect and those due to the fashion effect (i.e., the higher demand for products that are new). Our main findings are as follows: (1) the price and quantity of a new product tend to be higher than those of its predecessor at its exit from the market, implying that firms use new products as an opportunity to take back the price decline that occurred during the life of its predecessor under deflation; (2) a considerable fashion effect exists for the entire sample period, while the quality effect is declining over time; and (3) the discrepancy between the cost-of-living index estimated based on our methodology and the price index constructed only from a matched sample is not large.

JEL Classification Number: C43, E31, E32, O31

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1 Introduction

Central banks need to have a reliable measure of inflation when making decisions on monetary policy. Often, it is the consumer price index (CPI) they refer to when pursuing an inflation targeting policy. However, if the CPI entails severe measurement bias, monetary policy aiming to stabilize CPI inflation may well bring about detrimental effects on the economy. One obstacle lies in frequent product turnover; for example, supermarkets in Japan sell hundreds of thousands of products, with new products continuously being created and old ones being discontinued. Japan's Statistics Bureau (JSB) does not collect the prices of all these products. Moreover, new products do not necessarily have the same characteristics as their predecessors, so that their prices may not be comparable.

The purpose of this paper is to evaluate the effects of product turnover on a price index by using daily scanner, or point of sale (POS), data for Japan. To illustrate the importance of product turnover, let us look at price changes in shampoos. The thick line in Figure 1 shows the price of shampoos drawn from a *matched sample*, computed in a similar way to the CPI.[1] Here, a matched sample denotes a set of products that exist in two consecutive months and whose prices thus can be compared. The thick line shows a clear secular decline in the price of shampoo. On the other hand, the thin line depicts the unit price of shampoos. The unit price is defined as the total sales of shampoos divided by the total quantity of shampoos sold in all stores in a certain month, indicating how much a representative household spends on purchasing one unit of shampoo in that month. The figure shows that the unit price of shampoo rose in the early 1990s and has remained almost constant since the mid-1990s, indicating that there was no deflation, as far as the unit price is concerned.

Where does this difference come from? Figure 2 illustrates the reason. In Japan, product prices tend to decline over time since the price level at market entry (birth) $p(t'_b)$, and the price of a new product at entry (birth) $p(t_b)$ is generally higher than that of its predecessor at exit (death) $p(t'_d)$. In other words, firms recover the price decline in their products by introducing new products. The unit price incorporates both new and old products and hence increases when a high-priced new product enters into the market

[1] The CPI is compiled by calculating the ratio of the price of each product in a month to that in the previous month for a *comparable* product. To compare prices, therefore, the product needs to exist in two consecutive months. If a product is discontinued and replaced by a new noncomparable product, a quality adjustment is made. See, for example, Greenlees and McClelland (2011).

and a low-priced old product disappears. In contrast, when we calculate the average price of the matched sample, which is depicted by the red dashed line in the figure, we compare the prices of identical products only. The average price of the matched sample products continues to decline even if high-priced new products appear. This treatment would be valid if the quality difference between old and new products happens to coincide with the price difference between the two (i.e., the difference between the price of a product when it exits from the market and the price of its successor when it enters the market). On the other hand, if there is no quality change at the timing of product turnover, the unit price provides a precise cost-of-living index. Because the line of the CPI lies between other two lines in Figure 1, JSB seems to assume that quality changes explain almost half of the price increase when new products are introduced.

The main contribution of this paper is to develop methodology to construct a welfare-based cost-of-living index (COLI) that incorporates the following two effects at the time of product turnover. First, a successor product may be better (worse) in terms of its quality than its predecessor. In this case, the COLI should decline (increase) even if the price remains unchanged at the time of turnover. Second, consumers may have higher utility from buying a successor product simply because it is a new product, which is referred to as a fashion effect pointed out by Bils (2009).[2]

To distinguish the two effects in calculating the COLI, we borrow from Feenstra (1994) and Bils (2009). Feenstra (1994) proposes a method to incorporate the quality effect in calculating the COLI. Underlying this is the idea that if a new product has a higher sales share than its predecessor, this implies quality improvement. Thus, by comparing the sales share of both new and old products, we can quantify the rate of change in the COLI. However, his method does not incorporate the fashion effect. Even if a new product has a higher share, this may reflect the fashion effect, which is transitory, rather than a quality improvement. We therefore extend Feenstra's model to incorporate the fashion effect by assuming that consumers gain utility simply from purchasing a newly created product, even if its quality is the same as that of the product it replaces, and that this effect lasts for a finite period. We provide a new formula to compute the COLI that incorporates both the quality and fashion effects and apply this to the Japanese

[2]Bils (2009) provides the following example of the fashion effect: "Persons may prefer to consume a novel shortly after its arrival on the market, perhaps because they wish to discuss the book with others currently reading it, ... but we would not want to infer from this that novels are getting better and better."

scanner data.

We present three major stylized facts from the data and two results from the model-based analysis. The five stylized facts are as follows. First, the rate of product turnover is about 30 percent annually. This rate is higher than that in the United States. Second, successors tend to recover prices. The price of a new product at entry is about 10 percent higher than the exit price of the old product it replaced. Third, demand increases at entry are transitory and decay to half in a month, providing evidence of the fashion effect.

Empirical results based on our model can be summarized as follows. First, a considerable fashion effect exists for the entire sample period, while the quality effect is declining during the lost decades. Second, the discrepancy between the COLI estimated based on our methodology and the price index constructed only from a matched sample is not large, although the COLI estimated based on Feenstra's (1994) methodology is significantly lower than the price index constructed only from a matched sample.

There is a vast literature on the measurement of price indexes – be they consumer price or cost-of-living indexes – in the presence of product turnover with changes in quality. A seminal study is the Boskin Commission Report (1996), which estimates that the upward bias in inflation measured using the CPI is as large as 1%. While this study examines numerous reasons for the bias, Feenstra (1994) concentrates on the effects of product turnover and quality change on the price index, providing an analytical framework to calculate the COLI. His framework has its theoretical basis in the studies by Sato (1976) and Diewert (1976). Also see Melser (2006). Broda and Weinstein (2010) apply Feenstra's method to a wider variety of products to compare the COLI with the CPI. They argue that product turnover means that the "true" inflation rate measured using the COLI is 0.8 percentage points lower than that measured by the CPI. Greenlees and McClelland (2011) employ hedonic regression to construct a quality-adjusted CPI. As for Japan, Imai and Watanabe (2014) examine product downsizing as an example of quality retrogression and report that one third of product turnover during the decade preceding their study was accompanied by a size/weight reduction. Abe et al. (2015) decompose the effects of product turnover on the price index, but not the COLI.

Bils (2009) examines the measurement of price indexes in the presence of product turnover taking the fashion effect as well as the quality effect into account. He decomposes price changes at entry into the quality effect, the fashion effect, and a residual component and concludes that the quality effect accounts for two-thirds of the price increase when a new product replaces an old one. While his analysis does not consider welfare and he hence does not construct a COLI, we borrow his idea and calculate the COLI taking welfare into account. Meanwhile, Redding and Weinstein (2016) propose a unified approach to calculating the COLI under time-varying demand. The aim is to encompass not only the permanent and time-invariant quality effect but also the transitory and time-varying effect. Their model is complementary to ours in that their aim is very similar but uses different assumptions on household utility. It assumes no change in time-varying demand, on average, for goods that are in the sample in two consecutive months.

Studies using large-scale datasets of prices include Bils and Klenow (2004), Klenow and Kryvtsov (2008), Nakamura and Steinsson (2008), Klenow and Malin (2011), Melser and Syed (2015) among others. As for Japan, there are studies by Higo and Saita (2007), Abe and Tonogi (2010), Sudo, Ueda, and Watanabe (2014), and Sudo et al. (forthcoming). The last three studies use the same dataset as our study. The focus of these studies is mainly on price stickiness and appropriate pricing models.

The rest of the paper is organized as follows. Section 2 explains the scanner data we use in this paper. Section 3 provides stylized facts on product turnover and price changes. Sections 4 and 5 develop a model to compute the COLI and estimate quality change and fashion effects. Section 6 provides empirical results based on the model, while Section 7 concludes.

2 Data

This section provides an outline of the data we use, which is the POS scanner data collected by Nikkei. The data record the number of units sold and the amount of sales (price times the number of units sold) for each product i and retail shop s on a daily basis t. The observation period runs from March 1, 1988 to October 31, 2013. However, we use weekly data for November and December 2003 because daily data are missing. While the number of retailers increases during our observation period and reaches 300 at the end of the observation period, we limit our observations to 14 retailers that exist throughout the observation period to isolate the true effects of product turnover by excluding the effects of the increase in retailers. Products recorded include processed food and domestic articles. We have observations for 860,000 products in total, with an average of 100,000 products per year and 30,000 products per retailer per year.

The scanner data have two advantages over the CPI and one disadvantage.[3] First, they contain information on quantities as well as prices, enabling us to use Feenstra's (1994) method to calculate quality changes based on changes in sales shares. Second, the scanner data record all the products that are continuously created and destroyed as long as they are sold by the retailers in the dataset. In the CPI, only representative products are surveyed for each product category, and they are substituted only infrequently. One disadvantage of the scanner data is that their coverage of products is smaller than that in the CPI. Unlike the CPI, the scanner data exclude fresh food, recreational durable goods (such as TVs and PCs), and services (such as rent and utilities). Concretely, our scanner data cover 170 of the 588 items in the CPI. Based on data from the *Family Income and Expenditure Survey*, these 170 items make up 17 percent of households' expenditure. This narrow coverage somewhat limits the conclusions that can be drawn from our study, but the results nevertheless provide a clue regarding the extent of bias caused by product turnover.

[3]The procedure to treat product replacement in Japan's CPI is as follows. The JSB applies three different methods of quality adjustment at product turnover: (1) direct comparison, (2) direct quality adjustment, and (3) imputation. (1) Direct comparison is employed when new and old products are essentially the same. In this case, the price of the new product and the price of the old product are treated as if no product replacement occurred. On the other hand, (2) direct quality adjustment is employed when information about the change in quality between the old and new products is available. For example, if the old and new products differ only in terms of their quantity, and prices can be regarded to depend linearly on product quantity, the price of the new product is adjusted using the quantity ratio between the old and new products. This is referred to as the *quantity-ratio method* by the JSB. More generally, if information on product characteristics is available for the old and new products, a hedonic regression is applied to estimate quality adjusted prices. Another way to conduct direct quality adjustment is to use information on the observed price difference between the old and new products at a particular point in time. Specifically, if prices of the new and old products are available in months t and $t-1$ and it is safe to assume that the price difference between them reflects the quality difference between the old and new products, the price difference between the old and new products in $t-1$ is regarded as a measure of the quality difference and used to estimate the quality adjusted price of the new product in t. This is referred to as the *sample overlap method* by the JSB. Finally, (3) imputation is employed when neither information on product characteristics nor information on prices in $t-1$ and t is available. In this case, an estimate of constant-quality price change is made by imputation. Specifically, based on the assumption that the price change for the new product from $t-1$ to t is the same as price changes for the other products in the same item category, an estimate of the price of the old product in t is computed by multiplying the price of the old product in $t-1$ by the rate of inflation between $t-1$ and t for the other products belonging to the same item category.

Each product is identified by the Japanese Article Number (JAN) code indicating a product and its producer, together with its product name.[4] To see how the JAN code works, we look at margarine made by Meiji Dairies Corporation and its JAN code in Table 1. The first seven digits of the JAN code, 4902705, are the company code, while the last six digits vary product by product for the same margarine made by the same company. In the first two rows, the product names and quantities are exactly the same, while in the other rows the names differ, indicating different ingredients, packaging, and weights.

This example illustrates the difficulties in linking a successor product to a predecessor even for similar products made by the same firm. Moreover, from a household perspective, shoppers do not necessarily choose products from the same firm when old products disappear. Thus, in constructing the COLI, which should, by its nature, take the perspective of households, we choose the following two-step strategy to identify product generations. In the first step, we classify products into groups using the 3-digit product categories provided by Nikkei. There are 214 categories in total. Examples include yogurt, beer, tobacco, and toothbrushes. Importantly, the categories comprise products made by different manufacturers as long as the products fall into the same product category. The second step investigates time-series developments in the products in each category. If product A in a particular category disappears in one month and a new product B in the same category appears in the following month, then we regard A as the predecessor of B. Because there exist as many as 100,000 products each year and the 3-digit product categories are not very detailed, we are able to find a successor for most discontinued products. We use this method of linking in Sections 3 and 5. To check the robustness of our empirical results to changes in the methodology to link products, we employ a different method in which we link products only when the successor and predecessor products are produced by the same firm. See Appendix A for the method of aggregation and identification of product cycles in more detail.

Figure 3 provides another illustration of the use of the JAN code. In the figure, we count the number of products each year that have different JAN codes and are named "Kit Kat." "Kit Kat" is a chocolate-covered wafer biscuit bar produced by Nestlé. In

[4]The Distribution Systems Research Institute sets guidelines for the JAN coding, which ask firms to use different JAN codes for products that differ in terms of their labeling, size, color, taste, ingredient, flavor, sales unit, etc. It also encourages firms not to use the same JAN code for at least four years after old products cease to ship.

Japan, Nestlé sells a great number of "Kit Kat" products in different flavors such as Japanese tea (*maccha*), strawberry cake, bean jam, almond jelly, relaxing cacao, and so on. In 2008, there were more than 60 "Kit Kat" products. This example illustrates that Japanese consumers like product varieties and new products, which we think is responsible for the frequent product turnover and the considerable fashion effect in Japan, as we will discuss below.

3 Stylized Facts on Product Turnover and Price Changes

This section presents stylized facts on product turnover and price changes.

Stylized Fact 1: The product turnover rate is 30 percent annually, which is higher than that in the United States.

We first examine the degree of product creation and destruction and developments over time. The top panel of Figure 4 shows developments in the number of products over time. To construct the figure, we aggregate data over shops and directly count the number of products by the JAN codes. The figure indicates that the number of products roughly doubled. Notably, the number of products picked up from 1994, shortly after the collapse of the asset market bubble and the beginning of Japan's deflationary lost decades.

The bottom panel of Figure 4 shows developments over time in the annual rate of product entry and exit. The entry rate for each year is defined as the number of newly born products in the year divided by the total number of products in the year. Similarly, the exit rate is defined as the number of exiting products in the previous year divided by the total number of products in the previous year. We then aggregate these rates by assigning equal weights to all products, as explained in Appendix A.[5] The annual entry rates generally fluctuate in a range between $25-35$ percent, implying that products are replaced every three years on average. In most years, the entry rate exceeds the exit rate, leading to the increase in the total number of products shown in the top panel.[6]

[5]What is worth noting here is that we identify the timing of entry and exit of a product from the earliest and latest date of its sale, respectively, after aggregating its sales over shops. Also, results around 1988 and 2013 are subject to a censoring problem in that we cannot know the products that entered before March 1988 or exited after October 2013.

[6]In the figure, shaded areas represent Japan's recession periods. There is a tendency that, during recession periods, the entry rate declines while the exit rate jumps up, implying the procyclicality of

Comparing our results with those obtained by Broda and Weinstein (2010) suggests that product cycles in Japan are shorter than those in the United States. They calculate the rate of product turnover at the product level for the United States using home scanner data, reporting that the rates of product entry and exit are both 25 percent per year. We do the same calculation and the result is presented in Table 2, which is comparable to Table 3 in Broda and Weinstein (2010). The creation rate for each year is defined as the sales of newly born products in the year divided by the total sales of products in the year. Similarly, the destruction rate is defined as the sales of exiting products in the previous year divided by the total sales of products in the previous year. A comparison of the two tables shows that both the creation and destruction rates in Japan are around 40 percent per year, while they are less than 10 percent in the United States. Table 2 also presents entry and exit rates over four- and nine-year periods. The first and third (second and fourth) columns show that almost 85 (65) percent of products are not in the market nine (four) years later, which is again much higher than the corresponding US figure.

Because there exists heterogeneity in product turnover across products, we next compare product turnover between Japan and the United States at the product category level.[7] As shown in Figure 5, product turnover rates are higher in Japan than in the United States for all product categories. The figure also shows that there exists a tendency that products with a high turnover rate in the United States also have a high turnover rate in Japan. The Spearman rank correlation of 0.415, which is significant at the one percent level.

Stylized Fact 2: The price of a new product at entry exceeds that of its predecessor at exit.

Next, we compare prices and quantities sold between a predecessor and its successor and show them in Table 3 and Figure 6.

The top three rows in Table 3 show a typical price change of products, which we

product turnover. In the Online Appendix, we confirm this procyclicality by running a regression of the product turnover rate on sales growth at the 3-digit product category level.

[7]We thank Christian Broda and David Weinstein for sharing their data on product creation and destruction for about 1,000 product modules. Product categories are not the same between Japan and the United States, so we manually conduct category matching. Among the 214 product categories for the Japanese data, we successfully match 112 categories with the US counterparts.

calculate referring to Table 2 in Bils (2009). The unit-price inflation is calculated by taking the log prices for each year for each 3-digit product category, aggregating them with the sales weight, and taking the time-series mean of their annual changes. Bils (2009) decomposes the unit-price inflation into (1) contribution from price changes at scheduled rotations, (2) that from forced substitutions, and (3) that from inflation for continuously followed matched samples. Unlike his source data of the CPI, our scanner data do not distinguish between (1) and (2) but instead record all the products that are continuously created and destroyed as long as they are sold. We thus decompose the unit-price inflation into two: contribution from sample rotations (turnover, i.e. (1)+(2)) and that from within rotations (matched sample, (3)). Note that, because the number of exiting products differs from the number of entering products in each period, the sum of two components is not necessarily equal to the unit-price inflation. The table shows that the rate of unit-price inflation is positive, although it is close to zero at 0.25 percent per year. Price changes at sample rotations are positive, while price changes within rotations are negative. The former is greater than the latter, yielding the positive unit-price inflation.

We take a closer look at the price changes. We denote a predecessor by a prime ($'$) and the price of a predecessor at entry (birth) by $p(t'_b)$, that of a predecessor at exit (death) by $p(t'_d)$, and that of a successor at entry (rebirth) by $p(t_b)$. For each product, we then calculate the difference between the price at death and the price at birth for the predecessor (calculated as $\ln p(t'_d) - \ln p(t'_b)$), the difference between the successor's price at birth and the predecessor's price at death ($\ln p(t_b) - \ln p(t'_d)$), and the successor's and predecessor's price at birth ($\ln p(t_b) - \ln p(t'_b)$), and aggregate these across products by taking the sample mean. The top panel of Figure 6 plots developments in these price differences, with the horizontal axis representing the year in which a product was destroyed in the case of $\ln p(t'_d) - \ln p(t'_b)$ or reborn in the other two cases. The bottom three rows in Table 3 provide a summary about their sample mean.

The price difference $\ln p(t'_d) - \ln p(t'_b)$ depicted by the red line with circles is negative. It is on average -8.7 percent as Table 3 shows, indicating that products tended to experience a price decline over their life span. The line starts near zero in the early 1990s and decreases gradually to about 10 percent. This indicates that the size of price declines over the life span of a product increased as deflation became more entrenched.

The price of a new product at entry exceeds that of its predecessor at exit, as is shown by the positive $\ln p(t_b) - \ln p(t'_d)$ represented by the black line with squares. The price of a successor product at birth is ten percent higher than that of the predecessor product at death.

Finally, the blue line with triangles representing $\ln p(t_b) - \ln p(t'_b)$ indicates that, from about 2000 onward, the price of a new product at birth is more or less equal to that of its predecessor at birth. This pattern under deflation is different from that observed under inflation in the early 1990s. For the early 1990s, it is positive. In other words, when the overall CPI inflation rate was relatively high at about three percent, successors' prices tended to be higher than those of their predecessors. This seems to be a natural result under inflation and is in line with the price pattern for durable goods such as automobiles documented by Bils (2009) for the United States. However, this does not mean that the opposite pattern – namely, that the price of a new product at entry is below that of its predecessor at entry – can be observed in Japan during the period of deflation. Rather, there appear to be factors that prevent the price of a successor at entry falling below that of its predecessor at entry despite deflation, making the "rebirth price" sticky and creating asymmetry in the price setting for new products under inflation and deflation.

Taken together, these results suggest the following price pattern under deflation: after a product is born, its price falls and at some point the product is destroyed; the successor is then introduced at the same price as the predecessor at birth.[8]

What factors are responsible for this price pattern, in particular, the recovery of the decline in the price of predecessor products by successor products? An immediate candidate is quality improvements. If firms improve the quality of their product, this provides a justification for a higher price level. Another factor might be at play, namely, the fashion effect. Firms may be trying to attract consumers simply by introducing a new product, where the newness of the product is used as justification for the higher price.

This can be investigated in more details by looking at quantities purchased as well as prices. Suppose the price of a product increases. The quality improvement and fashion effects raise consumer demand for the product, while a price rise simply reflecting the

[8] Although we link products at the 3-digit product category, we admit that products can vary massively in their quality even within the same 3-digit product category. We thus checked the robustness of this result by linking only if successor products appear in the market one month after predecessor products exit from the market and if these predecessor and successor products are produced *by the same manufacturing firm*. However, we allow predecessor and successor products to belong to different 3-digit product categories in order to ensure a sufficient number of observations. We found that the pattern was very similar to that in Figure 6. See the Online Appendix for details on this.

firm's intention to bring the product price back up to its previous level would decrease demand. The quantity data in our scanner data are useful to determine which of these factors likely is at play. The lower panel of Figure 6 plots developments in the difference of quantities sold of predecessor and successor products in a similar way to the top panel. Specifically, we denote the quantity of the predecessor purchased at entry (birth) by $q(t'_b)$, that of the predecessor at exit (death) by $q(t'_d)$, and that of the successor at entry (rebirth) by $q(t_b)$. We then calculate quantity differences as $\ln q(t'_d) - \ln q(t'_b)$, $\ln q(t_b) - \ln q(t'_d)$, and $\ln q(t_b) - \ln q(t'_b)$. The black line with squares in the figure and Table 3 for $\ln q(t_b) - \ln q(t'_d)$ show that the quantity of new products purchased at entry is about $e^{0.546} - 1 \sim 70$ percent larger than that of the predecessor products purchased at exit. The quantity difference $\ln q(t'_d) - \ln q(t'_b)$ shown by the red line with circles is consistently negative at -0.532, suggesting that over the life span of a product the quantity purchased declines by about 40 percent. Finally, the blue line with triangles for $\ln q(t_b) - \ln q(t'_b)$ is stable around zero, suggesting that the quantity sold of a successor at entry is almost the same as that of its predecessor at entry.

This result suggests that firms can recover the price decline in their old product and bring the price back to the original level, since the successor at entry attracts greater demand than the predecessor at exit despite the higher price. In other words, consumers gain greater utility due to, for example, an improvement in quality or the fashion effect, contributing to a decrease in the welfare-based price index (COLI).

Stylized Fact 3: The demand increase at entry is transitory and decays to a half in a month.

As we saw in the lower panel of Figure 6, new products attract higher demand even though they have a higher price than their predecessor. A question one may ask would be how persistent the demand increase at entry is. If the quality improvement effect dominates the fashion effect, one would expect demand increases to be more long-lived. To examine whether this is the case, in Figure 7, we plot the price and quantity changes of products since entry in a logarithm scale, with the horizontal axis representing the number of months elapsed since the product was created. The axis starts with zero for the month of product creation ($t = 0$). We classify products depending on the length of their life (i.e., 2 months or longer, 16 months or longer, and 64 months or longer) and plot price and quantity changes for each category. The upper panel shows that product prices gradually decrease since entry, which is in line with the finding obtained in Figure 6. The lower panel shows that, despite this price pattern, quantity also decreases over time. Furthermore, the decrease is quite drastic: the quantity sold drops by about $e^{-0.4} - 1 \sim -30$ percent in the first month ($t = 1$). It drops to about a half ($\sim e^{-0.7} - 1$) of the initial value six months later for the products whose life spans are 16 months or longer. Products with longer life spans tend to experience a milder quantity decrease, but the quantity drops by 40 percent in six months since entry even for the products whose life spans are 32 months or longer.

This result can be regarded as evidence supporting the presence of fashion effects. As assumed by Bils (2009) in his model, new products attract consumers simply because they are new, but this fashion effect decays over time. An illustrative example of the fashion effect is "limited" products. In Japan, manufacturers sell many types of products with a "limited" label indicating that the product is available only in a particular region and/or at a particular time. For example, one type of potato chips has a butter soy sauce flavor and is sold only in Hokkaido prefecture, which is an area famous for butter production. Moreover, products are often "limited" in that they are sold only for a limited time, such as spring. Such limited products have gained huge popularity in Japan. Indeed, as Figure 8 shows, the number of products with the word "limited" (*gentei* in Japanese) in the name has increased rapidly. The popularity of such products can be seen as one reason product entry and exit rates are higher in Japan than in the United States.

4 Model to Calculate the COLI with Product Turnover

4.1 The COLI in a CES Setting

In this section, we introduce a model to calculate a welfare-based cost-of-living index. The model takes account of the following four effects on the COLI. First, when the price of products that have the same characteristics changes, the COLI changes (the price effect in the matched sample). Because many products experience a price decline over their life span, this effect tends to decrease the COLI. Second, when the price of newly entering products differs from that of old exiting products, the COLI changes (the price effect at entry). If firms recover the price decline of their products by introducing new products, the COLI increases. Third, when the quality of newly entering products differs from that of old exiting products, the COLI changes (the quality effect). In particular, the higher the quality of newly entering products, the more the COLI declines. Fourth, when new products enter the market, household utility increases temporarily, which lowers the COLI (the fashion effect).

To calculate the COLI taking these four factors into account, we extend the model developed by Feenstra (1994), who incorporates product turnover with the quality improvement effect, to further incorporate the fashion effect examined by Bils (2009). The COLI in Feenstra (1994) divides price movements into a common goods component and a variety adjustment due to entry and exit. An important thing to note is that, as for the former, the CES functional form gives researchers discretion as to which goods are considered common. We make extensive use of this fact in computing the COLI in an environment with quality and fashion effects. In what follows, we will show that one cannot directly apply Feenstra's method to an environment with quality and fashion effects, but one can still use a similar method if one makes an appropriate adjustment to the definition of common goods.[9] Specifically, we define common goods as those goods present in periods t and $t-1-\tau$ where τ is a positive parameter. Note that the Feenstra's original definition corresponds to the case of $\tau = 0$. See also Sato (1976), Diewert (1976), and Melser (2006) for the theoretical background of the COLI with product turnover.

The COLI is defined as the minimum cost of achieving a given utility, which we assume is expressed by the following constant elasticity of substitution (CES) function over a changing domain of products $i \in I_t$:[10]

$$C(p(t), I_t) = \left[\sum_{i \in I_t} c_i(t) \right]^{1/(1-\sigma)}, \tag{1}$$

where $c_i(t)$ represents the inverse of the cost associated with the purchase of product i in period t:

$$c_i(t) = \begin{cases} b_i \phi_i(t_i) \left[p_i(t)\right]^{1-\sigma} & \text{if } t_i < \tau \\ b_i \left[p_i(t)\right]^{1-\sigma} & \text{otherwise.} \end{cases} \tag{2}$$

Here, $\sigma > 1$ represents the elasticity of substitution, $p_i(t) > 0$ stands for the price of product i, $p(t)$ denotes its corresponding vector, and b_i represents the quality of or taste for product i.

The innovation in this specification compared to Feenstra (1994) is the introduction of the fashion effect $\phi_i(t_i)$, which increases household utility, where t_i represents time

[9] We appreciate a comment on this from an anonymous referee.

[10] To obtain this form, we need a homothetic CES utility function. See Lloyd (1975).

since the birth of a product (the elapsed time in the month of birth is zero). Bils (2009) assumes in his model that the fashion effect decays at a constant rate when a product is not renewed, while it jumps by a factor of 12 when a product is renewed after one year. Similar to Bils (2009), we assume that the fashion effect has a finite duration, but we do not assume any specific process regarding the speed of decay. Both a higher b_i and $\phi_i(t_i)$ increase utility and lower living cost $C(p(t), I_t)$ because of $\sigma > 1$. The difference between the two is that, while a quality improvement improves utility permanently as long as the product lasts, the fashion effect is transitory. Thus, all else being equal, the fashion effect on the rate of change in the COLI is almost neutral in the long run, because it decreases the COLI at the entry of a product but increases it after τ periods, like the effect of temporary sales on the price index. By contrast, the quality effect lowers the COLI in the long run. Thus, whether we incorporate the fashion effect or not on top of the quality effect can drastically change the COLI.[11]

As is well known, the CES function leads to the following convenient relationship:

$$\frac{p_i(t)q_i(t)}{\sum_{j\in I_t} p_j(t)q_j(t)} = \frac{c_i(t)}{\sum_{j\in I_t} c_j(t)}, \tag{3}$$

where $q_i(t)$ represents the quantity purchased of a product i in period t. See Appendix B for the proof. The left-hand side of equation (3) represents the sales share of a product i. Because the sales share is observable from our scanner data, this equation helps us to compute the COLI as well as quality and fashion effects.

[11] Another possible factor to explain the transitory demand for new products is seasonality. For example, ice cream is popular in summer, creating peak demand every 12 months. Such seasonality seems quantitatively small in our data because in the lower panel of Figure 7 we observe a small increase in quantity 12 months after entry.

4.2 The COLI with Quality Effects Only

As in Feenstra (1994), using equation (3), we can write a change in the COLI from $t-1$ to t as

$$\frac{C(p(t), I_t)}{C(p(t-1), I_{t-1})} = \frac{\left[\sum_{i\in I_t} c_i(t)\right]^{\frac{1}{1-\sigma}}}{\left[\sum_{i\in I_{t-1}} c_i(t-1)\right]^{\frac{1}{1-\sigma}}}$$
$$= \left[\frac{\sum_{i\in I_t} c_i(t)}{\sum_{i\in I_{t-1}\cap I_t} c_i(t)} \times \frac{\sum_{i\in I_{t-1}\cap I_t} c_i(t)}{\sum_{i\in I_{t-1}\cap I_t} c_i(t-1)} \times \frac{\sum_{i\in I_{t-1}\cap I_t} c_i(t-1)}{\sum_{i\in I_{t-1}} c_i(t-1)}\right]^{\frac{1}{1-\sigma}}$$
$$= \left[\frac{\sum_{i\in I_t} p_i(t)q_i(t)}{\sum_{i\in I_{t-1}\cap I_t} p_i(t)q_i(t)} \times \frac{\sum_{i\in I_{t-1}\cap I_t} c_i(t)}{\sum_{i\in I_{t-1}\cap I_t} c_i(t-1)} \times \frac{\sum_{i\in I_{t-1}\cap I_t} p_i(t-1)q_i(t-1)}{\sum_{i\in I_{t-1}} p_i(t-1)q_i(t-1)}\right]^{\frac{1}{1-\sigma}}. \tag{4}$$

Suppose for a moment that there is no fashion effect. Then, the second term in the right-hand side of equation (4) compares c_i in a common set, $I_{t-1} \cap I_t$, which is called a *matched sample*. In the matched sample, the quality vector b does not change from $t-1$ to t, and hence, we can compute this term using the conventional Sato-Vartia method following Sato (1976) and Vartia (1976):

$$\left(\frac{\sum_{i\in I_{t-1}\cap I_t} c_i(t)}{\sum_{i\in I_{t-1}\cap I_t} c_i(t-1)}\right)^{\frac{1}{1-\sigma}} = \prod_{i\in I_{t-1}\cap I_t} \left(\frac{p_i(t)}{p_i(t-1)}\right)^{w_i(t)}, \tag{5}$$

where the cost share is $s_i(t) = p_i(t)q_i(t)/\sum_{j\in I_{t-1}\cap I_t} p_j(t)q_j(t)$ and the weight $w_i(t)$ is given by

$$w_i(t) = \frac{\left(\frac{s_i(t)-s_i(t-1)}{\ln s_i(t)-\ln s_i(t-1)}\right)}{\sum_{j\in I_{t-1}\cap I_t}\left(\frac{s_j(t)-s_j(t-1)}{\ln s_j(t)-\ln s_j(t-1)}\right)}. \tag{6}$$

The first term in the right-hand side of equation (4) represents the inverse ratio of the sales of the products in t that exist both in $t-1$ and t to those that exist in t. In other words, the inverse equals one minus the fraction of sales of newly born products in t to total sales in t. The third term represents the ratio of the sales of products in $t-1$ that exist in both $t-1$ and t to those that exist in $t-1$. In other words, the ratio equals one minus the fraction of the sales of the products in $t-1$ that exit in t.

These two terms can be calculated as long as we have data on the sales shares of both newly entering and old exiting products. Thus, we can compute the rate of change in the COLI without knowing the quality parameter b, which is a contribution made by Feenstra (1994).

4.3 The COLI with Both Quality and Fashion Effects

We modify Feenstra's (1994) method to incorporate the fashion effect. In the presence of the fashion effect, the second term of the right-hand side of equation (4), $\sum_{i\in I_{t-1}\cap I_t} c_i(t) \Big/ \sum_{i\in I_{t-1}\cap I_t} c_i(t-1)$, is no longer in a common set. For example, a newly born product i in $t-1$ attracts households by the fashion effect of $\phi_i(0)$ in $t-1$, which changes to $\phi_i(1)$ in t. Therefore, we cannot simply apply the conventional method of using a matched sample to this case.

The key to resolving this problem is a selection of the true common set of $I_{t-\tau-1} \cap I_t$. Using equation (3), we have

$$
\begin{aligned}
\frac{C(p(t), I_t)}{C(p(t-1), I_{t-1})} &= \frac{\left[\sum_{i\in I_t} c_i(t)\right]^{\frac{1}{1-\sigma}}}{\left[\sum_{i\in I_{t-1}} c_i(t-1)\right]^{\frac{1}{1-\sigma}}} \\
&= \left[\frac{\sum_{i\in I_t} c_i(t)}{\sum_{i\in I_{t-\tau-1}\cap I_t} c_i(t)} \times \frac{\sum_{i\in I_{t-\tau-1}\cap I_t} c_i(t)}{\sum_{i\in I_{t-\tau-1}\cap I_t} c_i(t-1)} \times \frac{\sum_{i\in I_{t-\tau-1}\cap I_t} c_i(t-1)}{\sum_{i\in I_{t-1}} c_i(t-1)}\right]^{\frac{1}{1-\sigma}} \\
&= \left[\frac{\sum_{i\in I_t} p_i(t)q_i(t)}{\sum_{i\in I_{t-\tau-1}\cap I_t} p_i(t)q_i(t)} \times \frac{\sum_{i\in I_{t-\tau-1}\cap I_t} c_i(t)}{\sum_{i\in I_{t-\tau-1}\cap I_t} c_i(t-1)} \times \frac{\sum_{i\in I_{t-\tau-1}\cap I_t} p_i(t-1)q_i(t-1)}{\sum_{i\in I_{t-1}} p_i(t-1)q_i(t-1)}\right]^{\frac{1}{1-\sigma}}.
\end{aligned} \tag{7}
$$

As for the second term of the right-hand side, both the numerator and the denominator lie in the matched sample. The quality and fashion effects influence the numerator in exactly the same manner as the denominator, because the products are in $I_{t-\tau-1} \cap I_t$ and thus born at or before $t-\tau-1$. Therefore, this term can be calculated by the conventional Sato-Vartia method using the matched sample.

Note that the choice of the common set $I_{t-\tau-1} \cap I_t$ modifies the first and third terms slightly. The inverse of the first term represents one minus the fraction of sales of products in period t that are born from period $t-\tau$ to t. The third term represents one minus the fraction of sales of products in period $t-1$ that are born from period $t-\tau$ to $t-1$ or exit in period t.

As a special case, suppose

$$
\frac{\sum_{i\in I_{t-\tau-1}\cap I_t} p_i(t-1)q_i(t-1)}{\sum_{i\in I_{t-\tau-1}\cap I_t} p_i(t)q_i(t)} = \frac{\sum_{i\in I_{t-1}\cap I_t} p_i(t-1)q_i(t-1)}{\sum_{i\in I_{t-1}\cap I_t} p_i(t)q_i(t)}. \tag{8}
$$

If this holds for all $\tau = 1, 2, \cdots$, we can regard the fashion effect as continuing for an infinite period like a permanent improvement in quality and, in effect, do not exist. In this case, equation (7) reduces to Feenstra's (1994) equation, that is, equation (4), except for the difference in the matched sample in the second term.

4.4 Some Remarks

4.4.1 Comparison with Redding and Weinstein (2016)

Redding and Weinstein (2016) propose a "unified approach" to calculating the COLI under time-varying demand, which corresponds to the time-varying fashion effects in our model. In their model, they introduce a more general form of $c_i(t)$ defined as $c_i(t) = [p_i(t)/\varphi_i(t)]^{1-\sigma}$, where $\varphi_i(t)$ captures time-varying shifts in demand for product i. Like us, they point out that the second term in (4) is not in a common set under time-varying demand and consequently rewrite it as follows:

$$\ln\left(\frac{\sum_{i\in I_{t-1}\cap I_t} c_i(t)}{\sum_{i\in I_{t-1}\cap I_t} c_i(t-1)}\right) = \ln\left(\frac{\widetilde{p(t)}^*}{\widetilde{p(t-1)}^*}\right) + \frac{1}{1-\sigma}\ln\left(\frac{\widetilde{s(t)}^*}{\widetilde{s(t-1)}^*}\right) - \ln\left(\frac{\widetilde{\varphi(t)}^*}{\widetilde{\varphi(t-1)}^*}\right), \tag{9}$$

where a tilde over a variable denotes a geometric average and an asterisk indicates that the geometric average is taken for the set of common goods, such that $\widetilde{x(t)}^* \equiv \left(\Pi_{i\in I_{t-1}\cap I_t} x_i(t)\right)^{1/N_{t,t-1}}$ with $N_{t,t-1}$, that is, the number of goods in $I_{t-1}\cap I_t$. Note that time-varying demand $\widetilde{\varphi(t)}^*$ is unobservable.

They then introduce a new assumption that the geometric average of demand shifts is zero, that is,

$$\ln\left(\frac{\widetilde{\varphi(t)}^*}{\widetilde{\varphi(t-1)}^*}\right) = 0. \tag{10}$$

Note that the first and second terms in the right-hand side of equation (9) are observable, so that, with this assumption, one can easily calculate the COLI.

In other words, the approach taken by Redding and Weinstein (2016) is identical with that in Feenstra (1994) in decomposing price movements into a common goods term and a variety-adjustment term, but deviates from it when they construct a common goods index. Specifically, they do not rely on the conventional method proposed by Sato (1976) and Vartia (1976). In contrast, our methodology in constructing a common goods index is exactly the same as the Sato-Vartia method, although the definition of common goods differs from that used by Feenstra (1994).

Their model is complementary to ours in that it is very similar but uses different assumptions. We assume that for all products demand shifts stop varying after a finite period τ, while Redding and Weinstein (2016) assume no demand change on average. Which assumption is more appropriate depends on economic circumstances. For Japan, however, we believe that Figure 6 supports our estimation strategy, because we observe secular changes in pricing and product cycles even at an aggregate level, which runs counter to assumption (10). Moreover, Figure 7 shows that the spike in demand following the introduction of a new product that replaces an older one is short-lived and vanishes almost within six months, which is consistent with our assumption regarding the non-persistence of demand shifts even at an aggregate level, but not necessarily so with the assumption adopted by Redding and Weinstein (2016).

4.4.2 Consumer Learning

Our model is based on the assumption that consumers have perfect knowledge about products, as assumed in previous studies. However, as is studied by Shapiro (1983), Tirole (1988), Lu and Comanor (1998), Crawford and Shum (2005) and Bergemann and Välimäki (2006), in reality, there exist experience goods about which consumers have limited knowledge before they consume.[12] It is possible that consumers find the product not so attractive after their consumption. In this case, product demand is high at the time of product entry but decays over time, as we observed in the previous section (Stylized Fact 3).

One may wonder how this learning affects our procedure to measure the cost of living index. First, it is important to emphasize that our COLI is an *ex ante* measure of the cost of living in the sense that it is based on consumer's prior belief about products rather than their knowledge acquired through purchase and consumption. Therefore, high demand only at product entry, even if it is driven by the consumer's lack of knowledge, can still be regarded as a fashion effect. Second, with consumer learning, it is possible that consumers realize the quality of a product much better than they thought before purchase. In this case, the market share of this product would increase over its lifetime, which is something like a negative fashion effect. Our procedure to measure the cost of living is able to handle this negative fashion effect, in which the fashion parameter $\phi_i(t_i)$ is initially below one but converges to one over time.

5 Estimation of the Quality and Fashion Effects

To calculate the inflation rate based on the COLI, we use equation (7) and do not need to know the size of the quality and fashion effects. Nevertheless, they are very informative

[12] These papers are interested in firms' dynamic pricing for experience goods, while our study takes it given and analyzes the COLI from the household's perspective.

variables, so that we develop a method to estimate them.

Intuitively, the approach we take is to identify the quality change $b_i/b_{i'}$ by comparing the sales share between τ periods after an old product i' enters the market and τ periods after its successor product i enters the market, , where τ is the maximum duration of the fashion effect, as is assumed in the previous section. Because the fashion effect vanishes after a finite period elapses since the time of product entry, the difference in the two sales shares defined above provides information on the difference only in their quality.

We estimate both the level of and rate of change in the fashion effect. To estimate the level, that is, $\phi_i(0)$, we compare the sales share of product i at the time of entry and τ periods after entry. Because the same product naturally has the same quality, the difference in the sales share represents the fashion effect. In addition, we calculate the rate of change in the fashion effect, $\phi_i(0)/\phi_{i'}(0)$, to compare it with the quality change, $b_i/b_{i'}$. We estimate the rate of change in the fashion effect by comparing the sales share between the period when an old product i' enters the market and when the successor product i enters the market. At entry, product prices reflect both the quality and fashion effects, so the difference in the sales share implies $(b_i\phi_i(0))/(b_{i'}\phi_{i'}(0))$. Using the quality change that we previously obtained, we can estimate the rate of change in the fashion effect.

5.1 Quality Effect

Let us start by explaining more detail how we estimate the quality effect. We limit products' life span to τ or longer when estimating the change in quality. Suppose that product i enters the market in period t_b. Then, in period $t_b+\tau$, product i does not have the fashion effect, that is, $c_i(t_b+\tau) = b_i\left[p_i(t_b+\tau)\right]^{1-\sigma}$. Its predecessor i' exits in t'_d, where $t'_d = t_b - 1$ from our definition. Suppose that predecessor i' enters the market in period t'_b, where we again limit products' life span to τ or longer as $t'_b \leq t'_d - \tau$. Then, predecessor i' does not have the fashion effect in period $t'_b+\tau$, i.e., $c_{i'}(t'_b+\tau) = b_{i'}\left[p_{i'}(t'_b+\tau)\right]^{1-\sigma}$. Using equation (3) for $t_b+\tau$ and $t'_b+\tau$, we have

$$\frac{p_i(t_b+\tau)q_i(t_b+\tau)}{\sum_{j\in I_{t'_b}\cap I_{t_b+\tau}} p_j(t_b+\tau)q_j(t_b+\tau)} = \frac{c_i(t_b+\tau)}{\sum_{j\in I_{t'_b}\cap I_{t_b+\tau}} c_j(t_b+\tau)}$$

and

$$\frac{p_{i'}(t'_b+\tau)q_{i'}(t'_b+\tau)}{\sum_{j\in I_{t'_b}\cap I_{t_b+\tau}} p_j(t'_b+\tau)q_j(t'_b+\tau)} = \frac{c_{i'}(t'_b+\tau)}{\sum_{j\in I_{t'_b}\cap I_{t_b+\tau}} c_j(t'_b+\tau)}.$$

We choose the matched sample, $I_{t'_b} \cap I_{t_b+\tau}$, to compare c_j. Dividing the former equation by the latter yields

$$\frac{b_i}{b_{i'}} = \left[\frac{\frac{p_i(t_b+\tau)q_i(t_b+\tau)}{\sum_{j \in I_{t'_b} \cap I_{t_b+\tau}} p_j(t_b+\tau)q_j(t_b+\tau)}}{\frac{p_{i'}(t'_b+\tau)q_{i'}(t'_b+\tau)}{\sum_{j \in I_{t'_b} \cap I_{t_b+\tau}} p_j(t'_b+\tau)q_j(t'_b+\tau)}} \right] \left[\frac{p_{i'}(t'_b+\tau)}{p_i(t_b+\tau)} \right]^{1-\sigma} \left[\frac{\sum_{j \in I_{t'_b} \cap I_{t_b+\tau}} c_j(t_b+\tau)}{\sum_{j \in I_{t'_b} \cap I_{t_b+\tau}} c_j(t'_b+\tau)} \right]. \tag{11}$$

All the terms in the right-hand side of the equation are observable from our scanner data. Hence, we can estimate quality change $b_i/b_{i'}$. Note that more than one predecessor product may be paired with successor product i that enters the market in period t_b. In such a case, we compute the above $b_i/b_{i'}$ for each i' and take its unweighted mean with respect to all i'.

5.2 Fashion Effect

Next, we estimate the rate of change in the fashion effect. Again, we limit products' life span to τ or longer. Suppose that product i enters the market in period t_b with $c_i(t_b) = b_i\phi_i(0)\left[p_i(t_b)\right]^{1-\sigma}$ and its predecessor i' enters in t'_b with $c_{i'}(t'_b) = b_{i'}\phi_{i'}(0)\left[p_{i'}(t'_b)\right]^{1-\sigma}$. The same procedure as above leads to

$$\frac{b_i\phi_i(0)}{b_{i'}\phi_{i'}(0)} = \left[\frac{\frac{p_i(t_b)q_i(t_b)}{\sum_{j \in I_{t'_b-\tau} \cap I_{t_b}} p_j(t_b)q_j(t_b)}}{\frac{p_{i'}(t'_b)q_{i'}(t'_b)}{\sum_{j \in I_{t'_b-\tau} \cap I_{t_b}} p_j(t'_b)q_j(t'_b)}} \right] \left[\frac{p_{i'}(t'_b)}{p_i(t_b)} \right]^{1-\sigma} \left[\frac{\sum_{j \in I_{t'_b-\tau} \cap I_{t_b}} c_j(t_b)}{\sum_{j \in I_{t'_b-\tau} \cap I_{t_b}} c_j(t'_b)} \right]. \tag{12}$$

Once we know the quality change $b_i/b_{i'}$, we can estimate the rate of change in the fashion effect at entry, $\phi_i(0)/\phi_{i'}(0)$.

To estimate the level of the fashion effect, we assume that product i enters the market in period t_b with $c_i(t_b) = b_i\phi_i(0)\left[p_i(t_b)\right]^{1-\sigma}$ and exits in period $t_b+\tau$ with $c_i(t_b+\tau) = b_i\left[p_i(t_b+\tau)\right]^{1-\sigma}$, where we again limit products' life span to τ or longer as $t_d - t_b \geq \tau$. Then, the same computation yields the level of the fashion effect:

$$\phi_i(0) = \left[\frac{\frac{p_i(t_b)q_i(t_b)}{\sum_{j \in I_{t_b-\tau} \cap t_b+\tau} p_j(t_b)q_j(t_b)}}{\frac{p_i(t_b+\tau)q_i(t_b+\tau)}{\sum_{j \in I_{t_b-\tau} \cap I_{t_b+\tau}} p_j(t_b+\tau)q_j(t_b+\tau)}} \right] \left[\frac{p_i(t_b+\tau)}{p_i(t_b)} \right]^{1-\sigma} \left[\frac{\sum_{j \in I_{t_b-\tau} \cap I_{t_b+\tau}} c_j(t_b)}{\sum_{j \in I_{t_b-\tau} \cap I_{t_b+\tau}} c_j(t_b+\tau)} \right]. \tag{13}$$

6 Empirical Results

In this section, we apply the above model to the Japanese scanner data. We start by calculating time-series changes in the COLI at a monthly frequency. Next, we estimate the size of quality and fashion effects. Throughout this section, we employ the following parameter values. The elasticity of substitution σ is 11.5 based on Broda and Weinstein's (2010) estimate, although they mention that the demand elasticity typically lies between 4 and 7. The duration of the fashion effect τ, is 7 months based on the bottom panel of Figure 7. Later in this section, we will check the robustness of our results to changes in σ and τ.

6.1 The COLI

Figure 9 plots the monthly change in the COLI over time in an annualized rate. The line with triangles shows the COLI based on Feenstra's method, that is, equation (4), where the set of $I_{t-1} \cap I_t$ is treated as a matched sample. The line with circles shows the COLI using our method, that is, equation (7), where the set of $I_{t-\tau-1} \cap I_{t-1} \cap I_t$ is treated as a matched sample. The thin line represents the inflation rate for the matched sample that corresponds to the second term of equation (7) and is calculated by the Sato-Vartia method. While not shown in the figure, the inflation rate for the matched sampled based on Feenstra's method is very close to the thin line.

Let us first discuss the COLI based on Feenstra's method. The annual inflation rate for the matched sample is slightly negative and is close to the official CPI inflation rate. In contrast, the inflation rate based on the COLI constructed using Feenstra's method is much lower, fluctuating around -10 percent annually. As a result, the inflation rate based on Feenstra's method turns out to be consistently lower than that calculated for the matched sample. To understand why this happens, it is important to note that Feenstra's model assumes that high demand for a new product comes only from an improvement in quality if the price remains unchanged. Therefore, an increase in the market share of a product at the time of its entry to the market is always regarded as an indication of a quality improvement. Figure 9 indicates that the quality improvement measured based on Feenstra's assumption exceeds the extent to which firms recover the price decline of the predecessor product when they introduce a new product. Similar findings are obtained in previous studies including Broda and Weinstein (2010) and Melser (2006).

However, this result does not hold for the COLI based on our extended model. Figure 9 shows that incorporating the fashion effect eliminates the deflationary effect of changes in quality massively. The line with circle moves in parallel with the line with triangles but lies above it. In other words, Feenstra's method overestimates deflation. Intuitively, this difference arises because the fashion effect on the COLI is transitory, while the effect of quality changes is permanent. The fashion effect of new product i at time t on the COLI is deflationary from t to $t+\tau-1$, but disappears after $t+\tau$. Thus, the fashion effect reduces the change in the COLI at time t but increases it at time $t+\tau$. It thus makes a huge difference in the annual inflation rate between Feenstra's model and ours by about 10 percent points.

6.2 Comparison with Other Price Indexes

Table 4 compares the COLI in our model with five different price indexes, namely, the official CPI, the matched sample index, the 12-month matched sample index, the COLI based on Feenstra's method, and the COLI based on Redding and Weinstein's method. Note that, as for the CPI, we limit its coverage only to processed foods and daily necessities so that its coverage is the same as the scanner data. The inflation rate for the matched sample corresponds to the second term of equation (7) for the common set of $I_{t-\tau-1} \cap I_{t-1} \cap I_t$. Similarly, we compute the inflation rate for the 12-month matched sample. Specifically, we compute price changes for products that exist in the market at least for 12 months and apply the Sato-Vartia method. Note that this index is not influenced by the fashion effect since it excludes products with the life span less than 12 months. Finally, we calculate the COLI based on Redding and Weinstein (2016) as well as based on Feenstra (1994).

The table shows that the time-series mean of the change in the COLI in our model is -1.2 percent while corresponding standard deviation is 1.8 percent. The means inflation is highest for the official CPI, followed by the 12-month matched sample index, our COLI, the matched sample index, Feenstra's COLI, and Redding and Weinstein's COLI.

Figure 9 shows fluctuations in the inflation rate for the four indexes, indicating the following. First, the official CPI inflation is consistently higher by about one percent point than the inflation rate based on our COLI. Second, the inflation rate based on Feenstra's COLI is substantially lower than the inflation rate based on our COLI. The inflation rate based on Redding and Weinstein's COLI is even lower. Third, the inflation rate based on our COLI comoves with the inflation rate based on the matched sample. This suggests that the magnitude of the quality and fashion effects is closely correlated with the size of price change made by firms at the time of product entry. More specifically, the inflation rate based on our COLI is, on average, higher by one percent point than the inflation rate for the matched sample, suggesting that the downward impact due to the quality and fashion effects is slightly smaller than the price increase at the time of product entry. Somewhat surprisingly, the inflation rate based on our COLI is even closer to the inflation rate based on the 12-month matched sample, suggesting that the latter is a good approximation to the inflation rate based on our COLI.

6.3 Robustness Checks

We next examine the robustness of our result on the estimation of the COLI to various changes in model specifications. We first examine how the choice of the parameter for the duration of the fashion effect, τ, influences our result. In Figure 10 we compare the initiation rate based on our COLI and that for the matched sample for different values of τ ($\tau = 0$, 1, 4, and 7). Note that the case of $\tau = 0$ corresponds to Feenstra's COLI. The figure shows that the inflation rate for the matched sample increases as τ increases, albeit slightly. This is because longer-lived products tend to experience higher inflation rates. The larger τ is, the more is the matched sample dominated by longer-lived products, resulting in an increase in the inflation rate. Similarly, the inflation rate based on our COLI increases as τ increases.

It should be noted, for $\tau = 0$ and 1, the inflation rate based on our COLI is below the inflation rate for the matched sample, unlike in the other two cases. This is because a demand increase that lasts for more than zero or one month is regarded as caused by a quality improvement rather than due to the fashion effect, so that the inflation rate based on our COLI becomes lower. However, with a larger value for τ, the inflation rate based on our COLI becomes much higher than that for $\tau = 0$ or 1. Most importantly, the inflation rate based on our COLI is almost the same for $\tau = 4$ and 7, suggesting that the difference between our COLI and Feenstra's COLI is already reflected even when $\tau = 4$.

Table 4 shows the estimates of the COLIs under different specifications. We see that the estimate of the COLI does not change much even if we employ a much larger value for τ than our benchmark case ($\tau = 7$). When we use a lower value for σ than our benchmark ($\sigma = 11.5$), we find that the mean inflation rate based on our COLI becomes higher, deviating from the inflation rate for the matched sample. Specifically, for $\sigma = 4$, the mean inflation rate based on our COLI is 1.3 percent, which is much higher than the figure obtained under the benchmark value for σ. However, it should be noted that the sensitivity of the inflation rate based on our COLI to changes in σ is quantitatively smaller than that when we employ Feenstra's COLI. This stems from the fact that the discrepancy between the inflation rate based on our COLI and the inflation rate for the matched sample is significantly smaller than the case of Feenstra's COLI. For the case of Feenstra's COLI, this discrepancy is already large even when $\sigma = 11.5$, and a lower value of σ magnifies this discrepancy.

Next, we calculate the COLI by allowing the sample of retailer firms to change over time. So far we have limited our analysis to the 14 retailers that exist throughout the sample period. Although this was intended to distinguish the effect of product turnover from the effect of retailer turnover. However, this inevitably reduces the number of retailers. As an alternative treatment, we use information from all retailers available at a point in time but restrict the set of products we use to those that are available at more than two retailers. The second row from the bottom in Table 4 shows that the inflation rate based on our COLI changes only by less than one percent point.

Finally, we use a different definition about the timing of exit. In our analysis so far, we have defined the month of product exit as the last month when a product was sold. However, this treatment may overestimate the price decline at exit if products end their product life by a clearance sale. To avoid this, we instead define the month of product exit as the previous month when a product was sold, discarding observations in the last month. The last row in Table 4 shows that this change in the treatment about the timing of exit changes the estimated result on the COLI only by less than one percent point.

6.4 Quality and Fashion Effects

In this subsection we apply the method described in Section 5 to the Japanese data to estimate the quality and fashion effects. In this exercise, we link product predecessors and successors at the 3-digit product category level as explained in Section 2, rather than the individual product level (see Appendix C for the justification). We estimate the size of the quality and fashion effects for each month at the 3-digit product category level.

6.4.1 Quality Effect

The left panel of Figure 11 shows the histogram of the rate of change in product quality estimated based on equation (11), which is calculated as the time-series median of quality changes for each of the 3-digit product categories. Note that we take the median rather than the mean to minimize the measurement errors due to high volatility in sales and prices. The horizontal axis represents $b_i/b_{i'}$, where a value greater than one means an increase in quality and vice versa. The vertical axis represents the number of product categories. The density peaks at one, meaning that product quality remains more or less unchanged at entry. However, the distribution is not symmetric but skewed to the right, implying that some products experience significantly high quality changes. Turning to the right panel, it shows the rate of quality changes over time, which is calculated by taking the median of the quality changes for 3-digit product categories for each year.[13] The figure shows that, on average, it exceeds one, but it declines from two to one over the two decades. Together with the earlier findings, this suggests that the magnitude of quality improvement associated with the introduction of a new product becomes smaller as the number of products increases.

6.4.2 Fashion Effect

Next, the upper-left panel of Figure 12 shows the histogram of the estimated fashion effect across product categories. This is based on the time-series median of the estimated fashion effect for each of the 3-digit product category. We see that the histogram has a mode around two. On the other hand, the upper-right panel shows the evolution of the fashion effect over time, which is based on the median across product categories. These upper panels show that the estimated $\phi_i(0)$ is much greater than one, suggesting the presence of substantial fashion effects. Moreover, the fashion effect consistently increases during the sample period. Finally, the lower panel shows the rate of change in the fashion effect, namely $\phi_i(0)/\phi_{i'}(0)$ in equation (12). It shows that the rate of change is slightly higher than one but stable over time.[14]

6.5 Additional Evidence on Quality and Fashion Effects

To check the accuracy of our estimates on the quality and fashion effects, we conduct a couple of additional exercises. First, we compare our estimate of quality effect with

[13]Note that, in this figure, the birth year of successors, t_b, coincides with the year shown in the horizontal axis, but the birth year of predecessors, t_b', may be different depending on the year. The rate of change shown here is not the change in quality per year, but the change in quality over the product life.

[14]Note that the increase in the fashion effect over time is consistent with the increasing popularity of "limited" products in Figure 8. It may be the case that consumers' preference for "limited" products become stronger over time and firms have responded by offering more of such products.

that obtained using Feenstra's method. Specifically, we repeat the estimation of quality parameter $b_i/b_{i'}$ for different values of τ ($\tau = 1,\ 4$, and 7). We do this using our method and Feenstra's method. We then calculate the coefficient of correlation between the two monthly times series of $b_i/b_{i'}$, one from our method and the other from Feenstra's method, for each of the 3-digit product categories. The histogram of the coefficients of correlation across 3-digit product categories is shown in Figure 13. The estimated correlations are very close to one for most of the product categories, especially when τ is small. However, the correlation becomes weaker when τ is larger. This is because, in Feenstra's method, some part of the fashion effect is mistakenly recognized as a quality change.

Second, we check how the estimated quality and fashion effects (i.e., $b_i/b_{i'}$ and $\phi_i(0)$) are correlated with other variables, such as sales growth and product turnover. For example, we estimate the time-series median of $b_i/b_{i'}$ and product turnover for each of the 3-digit product categories, and calculate a cross-sectional correlation between the two variables. The variables we use in this exercise are as follows: gross creation rates (the sum of creation and destruction rates); net creation rates (the difference between creation and destruction rates); sales growth; the Herfindahl-Hirschman Index (HHI); price dispersion (the variance of posted prices for products belonging to a product category); and shopping frequency (how often consumers purchase). All the variables except for the last one are calculated using the scanner data, while the data on shopping frequency are taken from "Family Income and Expenditure Survey" published by the JSB in 2013. We conduct this exercise only for a subset of the entire product categories (186 product categories out of 214), so that, for each product category, we obtain the estimates of $b_i/b_{i'}$ and $\phi_i(0)$ for at least 300 months. For shopping frequency, we use an even smaller subset (107 categories), because the data on shopping frequency are only available for coarser categories than the scanner data.

The left panel in Figure 14 shows the scatter plot with quality growth on the horizontal axis and the net creation rate on the vertical axis, suggesting the presence of a positive correlation between the two variables. As shown in Table 5, the Spearman rank correlation between quality growth and net creation is positive at 0.189 and significantly different from zero.[15] Turning to the right panel, it shows that there is a positive correlation between the fashion effect and the gross creation rate. The coefficient of correlation between the two variables, which is presented in Table 5, is positive at 0.377

[15]Note that we use Spearman's rank correlation, which is less sensitive to strong outliers than Pearson's correlation.

and significantly different from zero.

Table 5 summarizes the results including those for the other variables. It shows that quality growth is positively correlated with net creation rates, sales growth, and price dispersion, while negatively correlated with shopping frequency. Net creation and sales growth may well be high in product categories with high quality growth, given that technological innovation is one of the most important driving forces for a sector to expand. The positive correlation with price dispersion is a natural outcome according to quality ladder models (e.g., Grossman and Helpman (1991) and Aghion and Howitt (1992)), because higher quality growth is considered to lead to higher heterogeneity in prices between old and new products. Finally, as for the negative correlation with shopping frequency, the result may not be so surprising, given that products with lower shopping frequency tend to be of higher durability, and that higher durability is associated with higher quality growth.

The column on the right of Table 5 shows that the magnitude of the fashion effect is positively correlated with gross and net creation rates, sales growth, and price dispersion while negatively correlated with the HHI. The positive correlation with gross creation may not be so obvious, but suppose that manufacturers recognize the presence of a fashion effect (i.e., high demand for new products) and seek to exploit it. Then they have an incentive to change products frequently. The positive correlation of the fashion effect with net creation or with sales growth can be explained similarly. However, it should be noted that consumers may find new products less attractive if product turnover is extremely high, because new products are no longer scarce. This would contribute to creating an inverse relationship between the fashion effect and product turnover. As for the positive correlation with price dispersion, it can be explained as in the case of quality growth and price dispersion.[16] Turning to the negative correlation with the HHI, this may be interpreted that manufacturers find it difficult to monopolize the market for those product categories with a higher fashion effect, because new products continuously enter the market and attract customers. This results in a lower HHI. Alternatively, a lower fashion effect may be a consequence of a higher HHI: consumers may not find a new product that much attractive for a product category in which a handful of products

[16] An alternative explanation is that lower price dispersion implies more homogeneity in products, so that even a new product is not that much different from the existing products. In this case, consumers may not find new products so attractive, which also leads to the positive correlation.

sell very well and dominate the market.[17]

Finally, we measure quality growth, $b_i/b_{i'}$, for those products that experience a change only in their size (e.g., weight or pieces in a bag) at the time of product turnover, but other attributes including brand names remain unchanged. A good thing in this case is that we have information about size changes at product turnovers, which come from product descriptions provided by Nikkei. Specifically, we borrow the dataset produced by Imai and Watanabe (2014), which use the same scanner data we use and identify 10,000 product turnovers that involve only size changes if any. One problem with their dataset is that the timing of a predecessor's exit and that of a successor's entry is often separate by more than six months. We pick 209 out of 10,000 product turnovers, in which such an entry lag is negligible. Note that, if a successor product differs from a predecessor product only in its size as well as the fashion effect, equation (2) changes to

$$c_i(t) = \begin{cases} \phi_i(t_i)\,[p_i(t)/x_i]^{1-\sigma} & \text{if } t_i < \tau \\ [p_i(t)/x_i]^{1-\sigma} & \text{otherwise.} \end{cases} \tag{14}$$

where x_i represents the size of product i. What we do this in this exercise is to estimate $b_i/b_{i'}$ without using the information regarding the change in the product size at the time of product turnover, and then compare it with $(x_i/x_{i'})^{\sigma-1}$. If a successor differs from a predecessor only in its size, $b_i/b_{i'}$ should coincide with $(x_i/x_{i'})^{\sigma-1}$. The estimation result indicates that the Spearman rank correlation between $b_i/b_{i'}$ and $(x_i/x_{i'})^{\sigma-1}$ is 0.204 with the p-value of 0.003 and that the elasticity of $\log(b_i/b_{i'})$ with respect to $(\sigma-1)\log(x_i/x_{i'})$ is 0.492. Also, Figure 15 shows that the ratio between $b_i/b_{i'}$ and $(x_i/x_{i'})^{\sigma-1}$ is located somewhere around one, indicating that our method successfully catches a product size change as a quality change.

7 Conclusion

In this study, we documented the pattern of product turnover in Japan and examined its effect on a welfare-based price index, namely, the COLI. Two particularly important

[17] Table 5 shows that the correlation of the magnitude of the fashion effect with shopping frequency is negative but not significantly different from zero. This may be interpreted as reflecting that consumers love to purchase new products simply because they purchase them infrequently. However, products with higher fashion effect may induce consumers to shop frequently to search for new products. This would contribute to creating a positive correlation between the two.

stylized facts are as follows. First, firms tend to use successor products to recover the price decline. Second, the increase in demand when a new product replaces an old product is transitory and decays to half within a month.

Our model incorporates not only quality but also fashion effects. Our results are as follows. First, we found that a considerable fashion effect exists for the entire sample period, while the effect of quality changes declined during the lost decades. Second, the discrepancy between the COLI estimated based on our methodology and the price index constructed only from the matched sample is not large, although the COLI estimated based on Feenstra's (1994) methodology is significantly lower than the price index constructed only from the matched sample.

Our findings help to explain why Japan managed to avoid falling into a severe deflationary spiral. During the two lost decades, Japanese firms introduced many new products into the market to recover the decline in the price of predecessor products. Even though quality improvements slowed down, the strategy worked because consumers were willing to pay the higher price due to the fashion effect.

In the future, we are hoping to extend our work mainly in two directions. The first is to apply our method to other economies such as the United States and the Euro area. This would help us to understand whether our results are peculiar to Japan, which experienced deflation. Second, we did not consider carefully the reasons for the price setting we observed or the reasons why firms retire products frequently and replace them with similar new ones. Important factors likely are the zero lower bound on nominal interest rates and deregulation in the retail market. Matsuura and Sugano (2009) and Abe and Kawaguchi (2010), for example, show that government policies in the 1990s relaxing entry regulations encouraged large retailers to enter the market. Endogenizing product turnover and investigating the causality between product turnover and price setting are important topics to be examined in the future.

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A Aggregation of Variables and Identification of Product Entry and Exit

A.1 Aggregation

In this study, we aggregate variables of interest over days, products, and shops in the following way.

1. We aggregate a variable, such as the sales amount and quantities sold of each product, over shops.
2. We take the daily average of a variable by dividing it by the number of days in each month.
3. Aggregation over products
   (a) For Table 3 and Figure 6, we first compare prices and quantities sold between predecessors and successors in each 3-digit product category. We then aggregate them over the 3-digit product categories, using the weight given by the number of entering and exiting products in each month.
   (b) To construct the COLI, we use the formula explained in the main text for products in each 3-digit product category. We then aggregate the COLI at the 3-digit product category level using the sales weight.
   (c) Otherwise, we take the logarithm of a variable (unless it is a rate of change or ratio) and then aggregate the values over products, assigning equal weights to all products.

The reason for aggregating over shops first is to mitigate chain drift. As highlighted by Feenstra and Shapiro (2003), the durability of goods and households' desire to hold inventories create considerable chain drift in the chained price index. Also see Ivancic, Diewert, and Fox (2011).

A.2 Identifying the Entry and Exit of Products

We explain how we identify the date of birth (entry) and death (exit) of a product. As for the former, after aggregating sales amounts and quantities sold over shops, we record the earliest date when a product was sold and denote this as the date of birth (entry)

t_b. We then calculate its sales amounts and quantities sold per day by dividing sales and quantities by the remaining days of the month, that is, $t_m - t_b + 1$, where t_m represents the days of the month. This provides the quantity $q(t_b)$ per day in the month of birth (entry). The price $p(t_b)$ is computed by dividing sales per day by the quantity sold per day. We use posted prices, not regular or temporary sales prices.

Similarly, the date of death (exit) t_d is defined as the last date when a product was sold. Sales and quantities per day are calculated by dividing sales and quantities by t_d. This provides us with the quantity $q(t_d)$ per day and the price $p(t_d)$ in the month of death (exit). In other months of the product cycle, the quantity per day and the price are defined as the quantity sold divided by the days of the month and sales divided by the quantity sold, respectively.

B Proof of Equation (3)

Using Shephard's Lemma, we have the following equation for the quantity $q_i(t)$ sold of product i from equation (1):

$$\begin{aligned} q_i(t) &= \frac{\partial C(p_t, I_t)}{\partial p_i(t)} = \frac{1}{1-\sigma} \left[\sum_{i \in I_t} c_i(t) \right]^{\frac{1}{1-\sigma}-1} \frac{\partial c_i(t)}{\partial p_i(t)} \\ &= \frac{1}{1-\sigma} C(p_t, I_t)^{\sigma} A_i(t_i)(1-\sigma) \left[p_i(t) \right]^{-\sigma}, \end{aligned}$$

where $A_i(t_i)$ encompasses quality and fashion effects for product i, which are independent of $p_i(t)$. This yields

$$\begin{aligned} p_i(t) q_i(t) &= C(p_t, I_t)^{\sigma} A_i(t_i) \left[p_i(t) \right]^{1-\sigma} \\ &= c_i(t) C(p_t, I_t)^{\sigma}, \end{aligned}$$

leading to

$$\frac{p_i(t) q_i(t)}{c_i(t)} = C(p_t, I_t)^{\sigma}.$$

The right-hand side of the equation is independent of i, and we thus obtain equation (3).

C When Product Generations are not Tracked One-to-One

The model in the main text assumes full information on product generations: a product i' is known to be the predecessor of a product i. However, our scanner do not allow us to match product generations one-to-one for all products.

Nevertheless, we can still estimate the quality and fashion effects. To see this, we take the logarithm of equation (11):

$$\ln \frac{b_i}{b_{i'}} = \ln \frac{p_i(t_b+\tau)q_i(t_b+\tau)}{\sum_{j\in I_{t'_b}\cap I_{t_b+\tau}} p_j(t_b+\tau)q_j(t_b+\tau)} - \ln \frac{p_{i'}(t'_b+\tau)q_{i'}(t'_b+\tau)}{\sum_{j\in I_{t'_b}\cap I_{t_b+\tau}} p_j(t'_b+\tau)q_j(t'_b+\tau)}$$
$$+ (1-\sigma)\left[\ln p_{i'}(t'_b+\tau) - \ln p_i(t_b+\tau)\right] + \ln \left[\frac{\sum_{j\in I_{t'_b}\cap I_{t_b+\tau}} c_j(t_b+\tau)}{\sum_{j\in I_{t'_b}\cap I_{t_b+\tau}} c_j(t'_b+\tau)}\right].$$

The first and second terms in the right-hand side can be computed without one-to-one matching of product generations. Taking the average across products i and i', we have

$$\left\langle \ln \frac{b_i}{b_{i'}} \right\rangle = \left\langle \ln \frac{p_i(t_b+\tau)q_i(t_b+\tau)}{\sum_{j\in I_{t'_b}\cap I_{t_b+\tau}} p_j(t_b+\tau)q_j(t_b+\tau)} \right\rangle - \left\langle \ln \frac{p_{i'}(t'_b+\tau)q_{i'}(t'_b+\tau)}{\sum_{j\in I_{t'_b}\cap I_{t_b+\tau}} p_j(t'_b+\tau)q_j(t'_b+\tau)} \right\rangle$$
$$+ (1-\sigma)\left[\langle \ln p_{i'}(t'_b+\tau)\rangle - \langle \ln p_i(t_b+\tau)\rangle\right] + \left\langle \ln \left[\frac{\sum_{j\in I_{t'_b}\cap I_{t_b+\tau}} c_j(t_b+\tau)}{\sum_{j\in I_{t'_b}\cap I_{t_b+\tau}} c_j(t'_b+\tau)}\right] \right\rangle,$$

where $\langle z_i \rangle$ represents an operator to take the average of z_i across i. Even if the number of products i denoted by N differs from that of products i' denoted by N', the above equation holds true, as long as the probability that a product in i' changes to a product in i equals $1/N$.

Table 1: JAN Codes and Product Names of Margarine Made by Meiji Dairies Corporation

JAN codes	Product names
4902705092709	Meiji Corn Soft Half 120g
4902705100374	Meiji Corn Soft Half 120g
4902705066915	Meiji Corn Soft with Butter 400g
4902705104280	Meiji Corn Soft with Butter 300g
4902705001541	Meiji Corn Soft Fat Spread 225g
4902705001558	Meiji Corn Soft Fat Spread 450g
4902705100275	Meiji Corn Soft Fat Spread 180g
4902705100336	Meiji Corn Soft Fat Spread Box 400g
4902705105379	Meiji Corn Soft Fat Spread (Weight Increased) 320+20g
4902705106383	Meiji Corn Soft Fat Spread 160g

Table 2: Product Entry and Exit

	9-year 1991–2000	4-year 1996–2000	9-year 2001–2010	4-year 2006–2010	1-year median
Entry rate	0.877	0.691	0.861	0.668	0.317
Creation rate	0.869	0.635	0.853	0.703	0.425
Exit rate	0.854	0.629	0.847	0.683	0.291
Destruction rate	0.845	0.662	0.863	0.714	0.399

Note: Entry rate = Number of new JAN codes (t) / total number of JAN codes (t); Exit rate = Number of disappearing JAN codes ($t-1$) / total number of JAN codes ($t-1$); Creation rate = Sales of new JAN codes (t)/ total sales (t); Destruction rate = Sales of disappearing JAN codes ($t-1$) / total sales ($t-1$)

Table 3: Price and Quantity Changes over the Product Cycle

	Price change	Quantity change
π unit price	0.0025	–
$= \pi$ sample rotations (turnover)	0.0085	–
$+\pi$ within-rotations (matched)	-0.0065	–
From birth predecessor to death predecessor	-0.083	-0.532
From death predecessor to birth successor	0.095	0.546
From birth predecessor to birth successor	0.012	0.015

Table 4: COLI Changes (Inflation Rates) under Different Specifications

	Mean	Standard deviation
COLI (τ=7, σ=11.5)	−0.012	0.018
CPI	0.001	0.015
12-month matched sample (Sato-Vartia)	−0.005	0.018
Matched sample (Sato-Vartia)	−0.022	0.017
COLI by Feenstra (1994)	−0.107	0.022
COLI by Redding and Weinstein (2016)	−0.142	0.025
τ=1	−0.040	0.019
τ=4	−0.017	0.018
τ=14	−0.017	0.019
σ=4	0.013	0.038
σ=8	−0.007	0.021
Feenstra (1994) w/ σ=4	−0.284	0.048
Feenstra (1994) w/ σ=8	−0.142	0.027
All retailers	−0.018	0.018
The timing of exit is one month before the last sale of the product	−0.021	0.018

Note: Matched sample corresponds to the second term of equation (7).

Table 5: Cross Sectional Correlations of the Quality/Fashion Effect with Various Variables

	$b_i/b_{i'}$	$\phi_i(0)$
Creation + destruction rate	−0.011 (0.878)	0.377*** (1.47 10^{-7})
Creation − destruction rate	0.189*** (0.010)	0.219*** (0.003)
Sales growth	0.176** (0.017)	0.161** (0.028)
HHI	−0.111 (0.132)	-0.162** (0.027)
Price variance	0.223*** (0.002)	0.294*** (4.96 10^{-5})
Shopping frequency	−0.212** (0.035)	−0.148 (0.144)

Note: *** and ** represent significance at the 1 and 5 percent levels, respectively. Figures in parenthesis indicate the p-values.

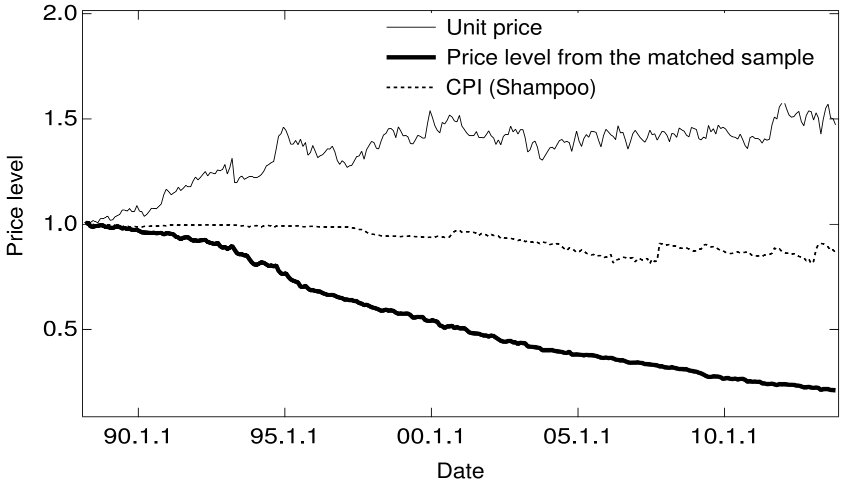

Figure 1: Various Measures of Shampoo Prices

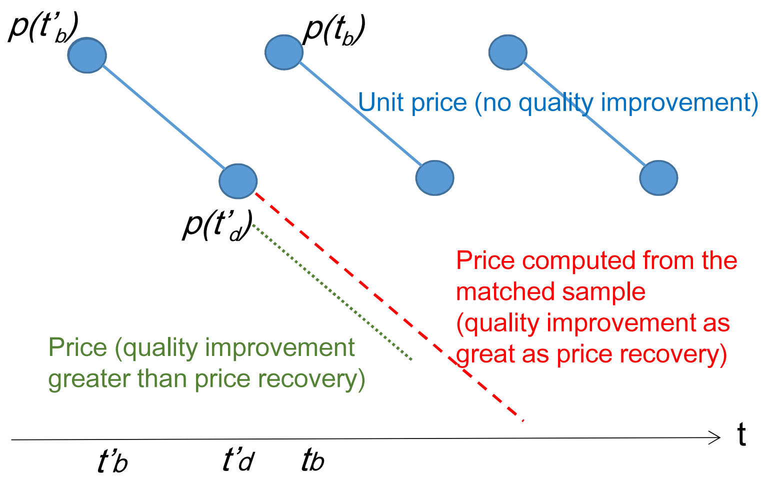

Figure 2: Price Changes within and between Product Lives

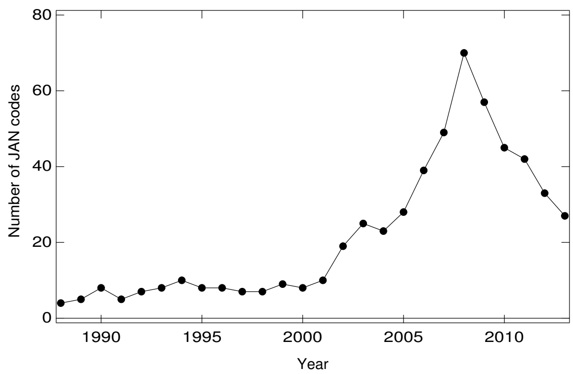

Figure 3: Number of "Kit Kat" Products

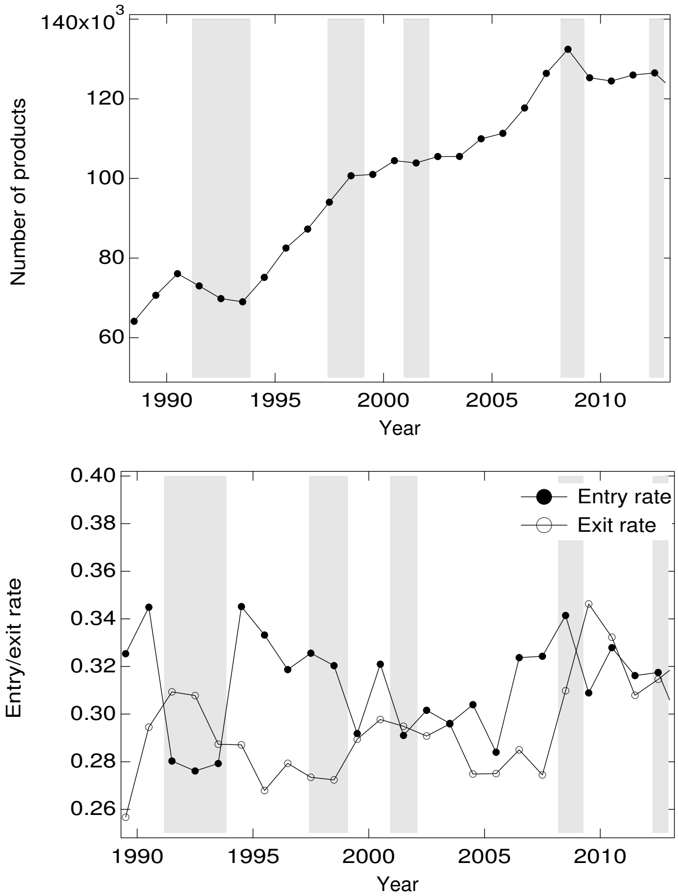

Figure 4: Number of Products (top) and Entry and Exit Rates (bottom)

Note: Shaded areas represent Japan's recession periods.

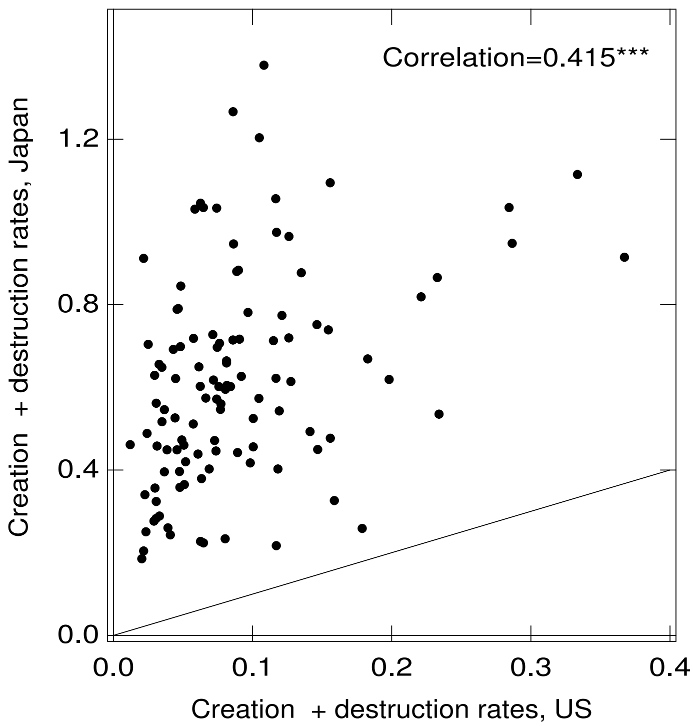

Figure 5: Creation and Destruction Rates in Japan and US

Note: Each dot represents Japan's 3-digit product category. Data for the sum of creation and destruction rates in the Unitd States are taken from the home scanner data and reported by Broda and Weinstein (2010). The line represents the 45 degree line.

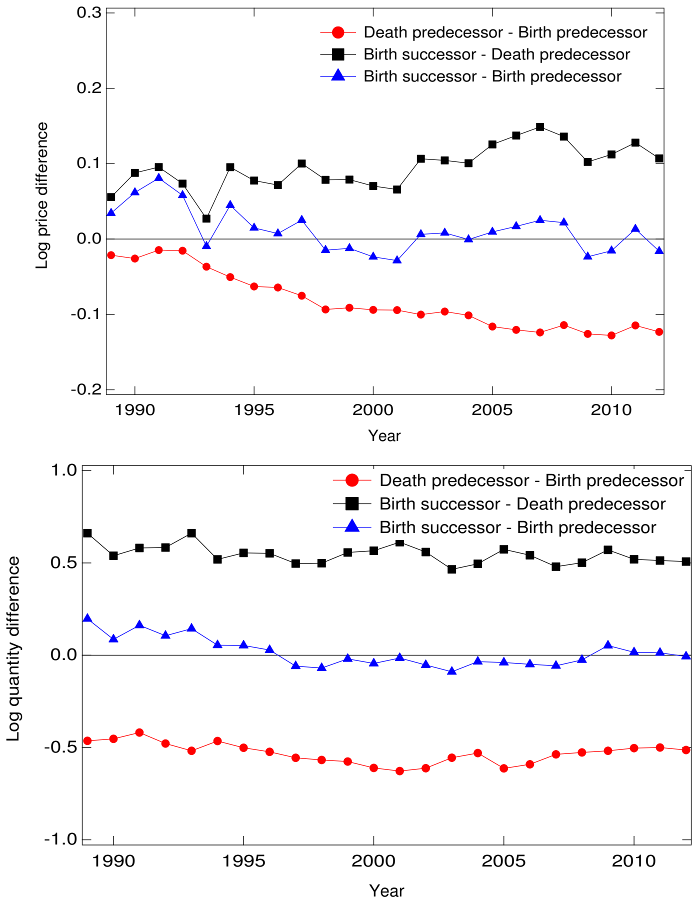

Figure 6: Price and Quantity Changes over the Product Cycle

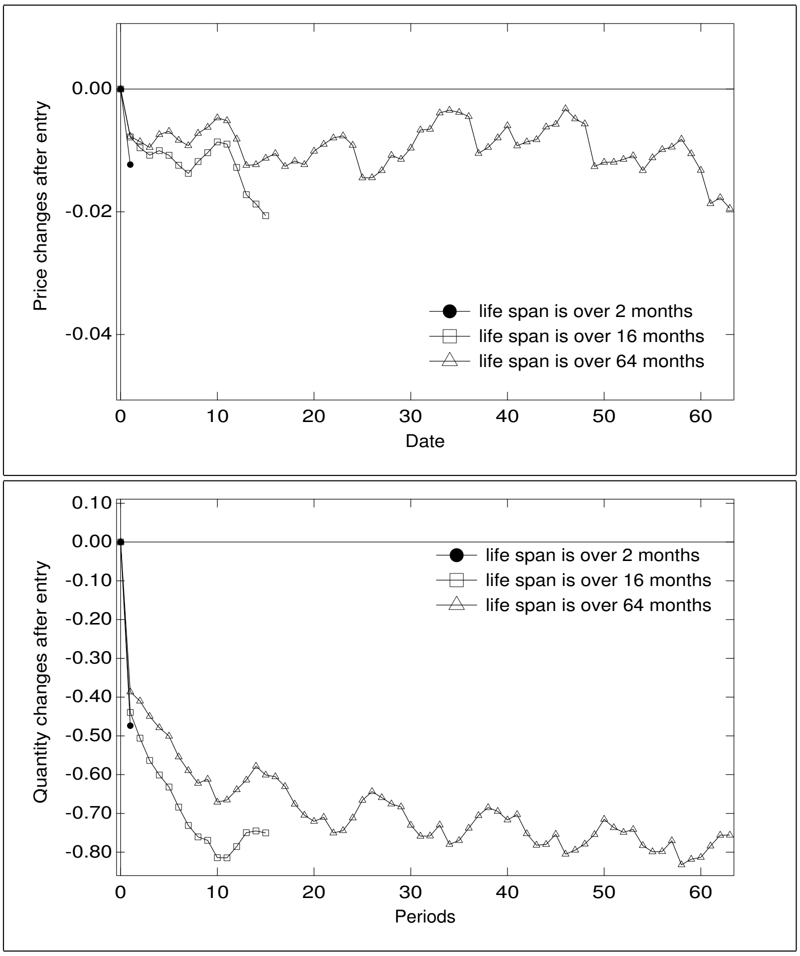

Figure 7: Price and Quantity with the Time Elapsed since Product Entry

Note: The horizontal axis represents the number of months elapsed since products are created, while the vertical axis represents price and quantity changes in a logarithm scale. Three lines represent those for the products whose life spans are 2, 16, and 64 months or longer.

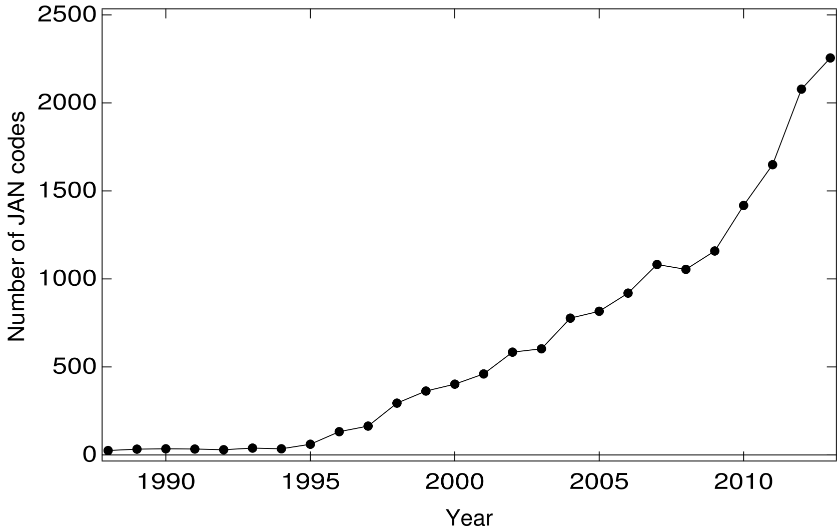

Figure 8: Number of “Limited” Products

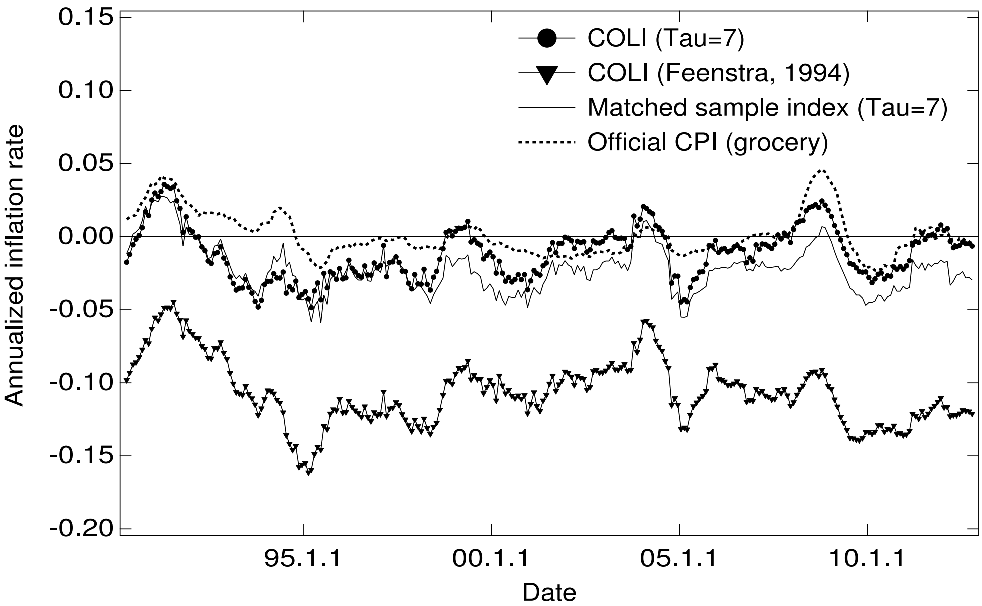

Figure 9: The Estimate of the COLI

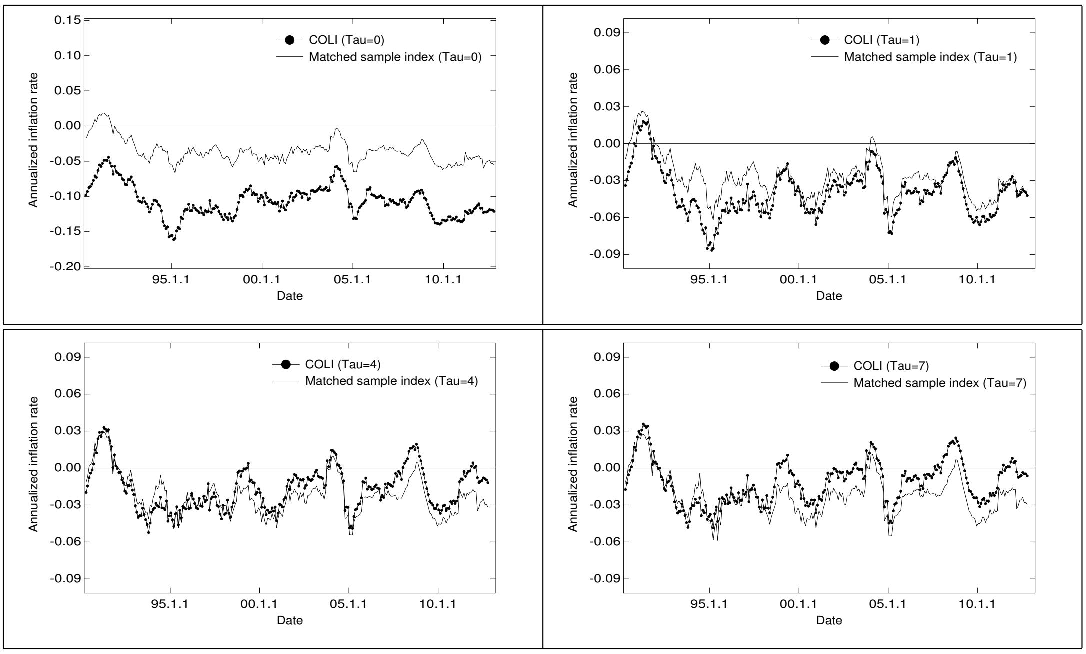

Figure 10: The COLI under Different τ

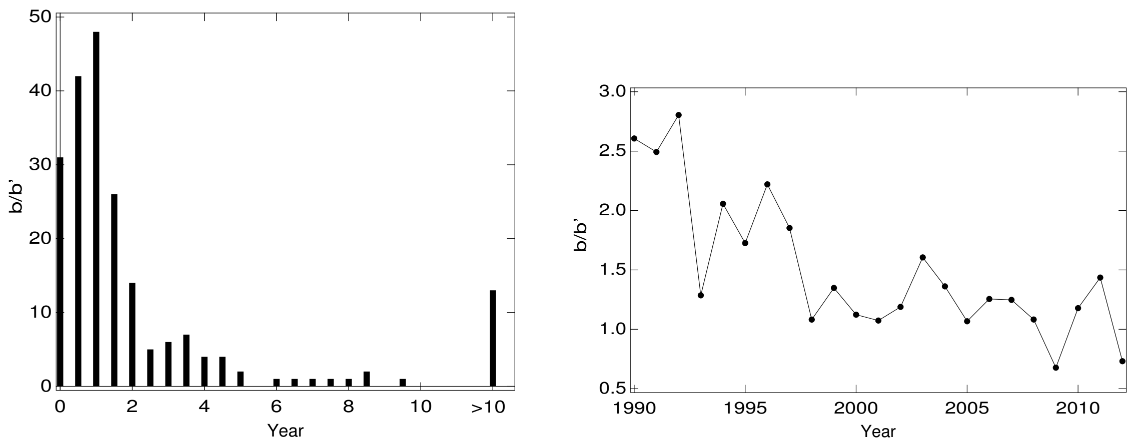

Figure 11: Quality Effect

Note: The left panel shows the histogram of changes in quality, while the right panel shows developments in quality changes over time.

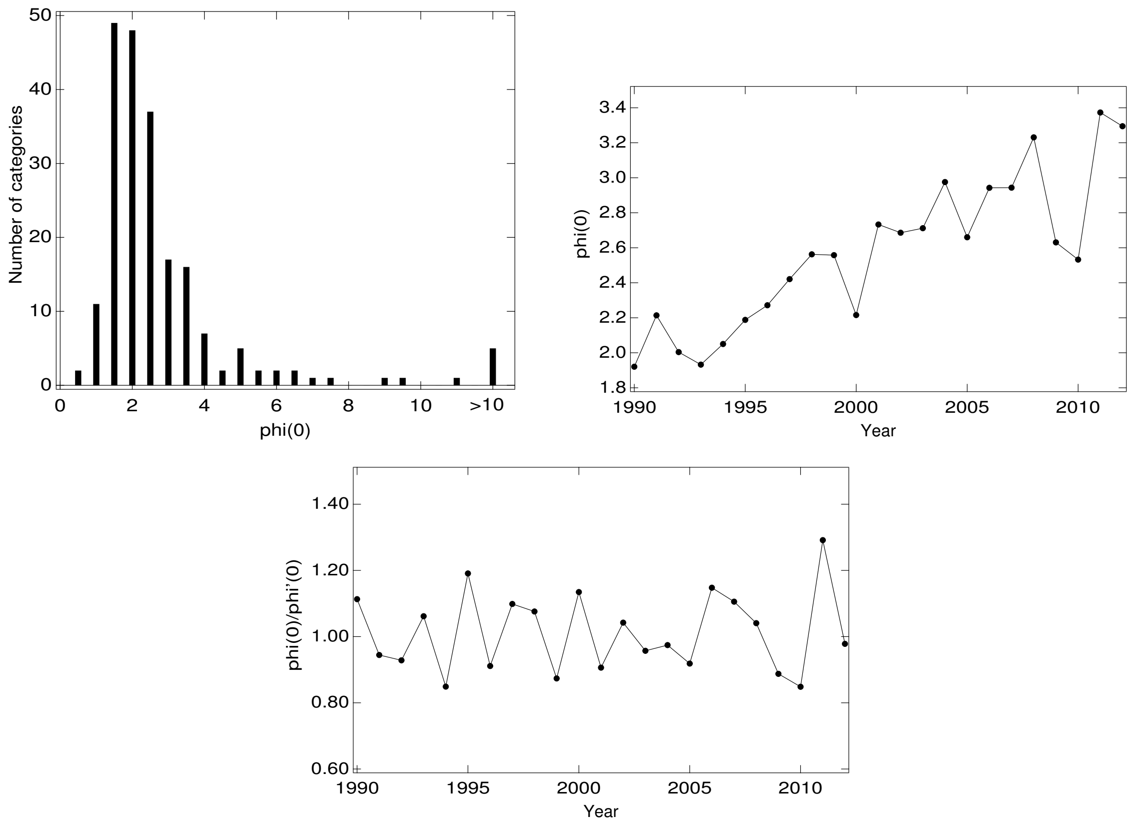

Figure 12: Fashion Effect

Note: The upper-left panel shows the histogram of the fashion effect, while the upper-right panel shows developments over time. The lower panel shows developments in the rate of change in the fashion effect.

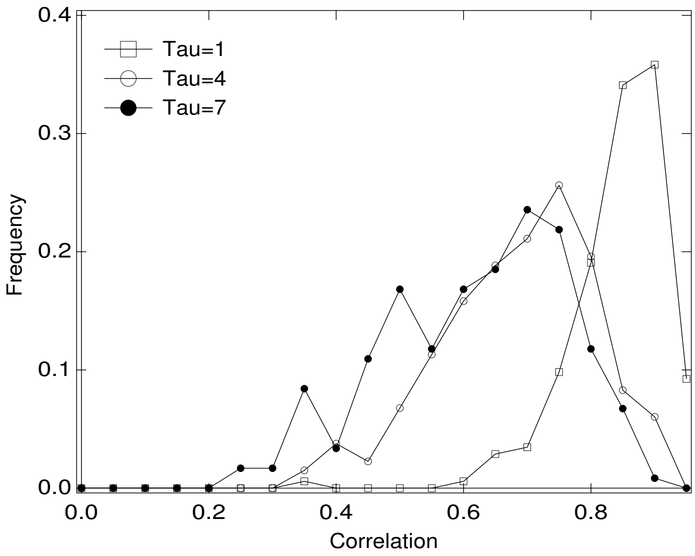

Figure 13: Correlations between the Quality Effect Based on Feenstra's Method and That Based on Our Method

Note: To draw this, we first calculate the time-series correlations of quality growth estimated by Feenstra's method and that by our method at the 3-digit product category and then show their histogram.

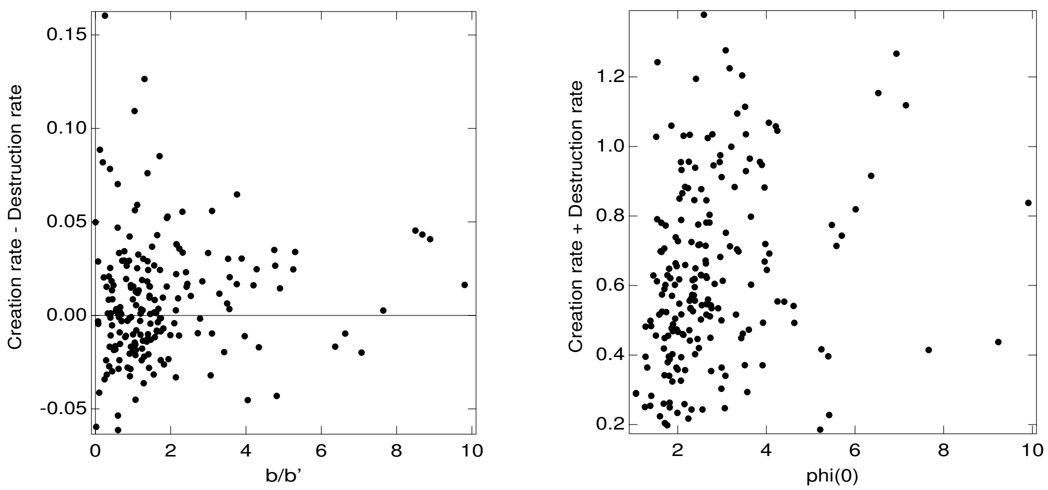

Figure 14: Cross Sectional Correlation between Quality Growth and Net Creation (Left) and between Fashion Effect and Gross Creation

Note: The left panel shows the scatter plot of the net creation rate and quality growth. The right panel shows the scatter plot of the gross creation rate and the fashion effect. Each dot represents the 3-digit product category.

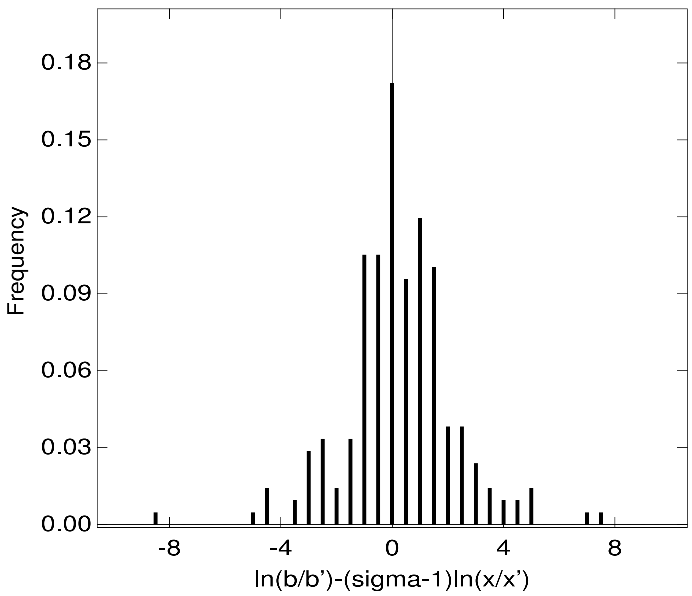

Figure 15: Quality Growth and Size Changes

Note: The figure shows the histogram of the log difference between quality growth $b_i/b_{i'}$ and size changes $(x_i/x_{i'})^{\sigma-1}$ for 209 product turnovers that involve only size changes if any.