Product Turnover and Deflation: Evidence from Japan

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Abstract

In this study, we evaluate the effects of product turnover on a welfare-based cost-of-living index. We first present several 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 a new method 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: (i) 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 Japanese firms use new products as an opportunity to take back the price decline that occurred during the life of its predecessor under deflation; (ii) a considerable fashion effect exists for the entire sample period, while the quality effect is declining over time; and (iii) 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.

Keywords: cost-of-living index; product creation and destruction; quality adjustments; fashion effect; substitution; lost decades

JEL classification: 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 the CPI inflation rate 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.

In this paper, we aim to evaluate the effects of product turnover on a price index by employing 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 corresponds to 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. The graph reveals that the unit price of shampoo rose in the early 1990s and has remained almost constant since the mid-1990s. We therefore observe no deflation. Finally, the price of shampoos reported in the CPI, represented by the dashed line in the graph, moves between the two lines.

Why does this difference arise? 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

[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).

products by introducing new products. The unit price incorporates both new and old products and hence increases when a high-priced new product appears 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.

In addition to the measurement of the price index, our study aims to shed new light on Japan's deflation from the perspective of product turnover. Japan is unique in that the Japanese economy experienced prolonged deflation from the mid-1990s onwards. On average, the CPI fell by 0.3% annually from 1999 to 2012. In this study, we address at what level prices are set when products are created compared to disappearing products, how their prices develop before they are discontinued, and how these price patterns changed during the lost decades. Moreover, we consider why deflation has been mild and Japan avoided a deflationary spiral.

To this end, we employ Japanese scanner data from March 1988 to October 2013 and document the pattern of price changes over the product cycle. We then construct a welfare-based price index, or cost-of-living index (COLI), that incorporates product turnover taking the quality and fashion effects into account. A successor product may be better in terms of its quality than its predecessor; or consumers may derive utility simply from buying a new product, as highlighted by Bils (2009).[2] Both aspects naturally lead to an increase in welfare and thus result in a decrease in the COLI.

It is thus particularly important to separate the quality and fashion effects from the

[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."

price effect in calculating the COLI when an old product is replaced by a new one. In that regard, 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 pointed out by Bils (2009). 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 then provide a formula to compute the COLI that incorporates both the quality and fashion effects and apply this to Japan.

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% 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% 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.

Meanwhile, the model-based analysis shows the following. First, we find that 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 two studies use the same dataset as our study. The focus of these studies is mainly on price stickiness and appropriate pricing models.

The structure of this paper is as follows. Section 2 explains the scanner data. Section 3 provides stylized facts on product turnover and price changes. Section 4 develops a model to compute the COLI and estimate quality change and fashion effects. Section 5 applies the model to Japan, while Section 6 concludes.

2 Data

This section provides an outline of the data we use, which is the POS scanner data collected by Nikkei Digital Media. 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,

[3]It is important to know how the CPI in Japan is compiled when product replacement takes place. 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.

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% 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.

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 company. Moreover, from a household perspective, shoppers do not necessarily choose products from the same company 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 codes provided by Nikkei Digital Media. There are 214 groups in total. Examples include yogurt, beer, tobacco, and toothbrushes. Importantly, the groups comprise products

[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.

made by different manufacturers as long as the products fall into the same product group. The second step investigates time-series developments in the products in each group. If product A in a particular group disappears in one month and a new product B in the same group 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 groups are not very detailed, we are able to find a successor for most discontinued products. In Appendix A, we explain the method of identification of product cycles in more detail. We use this method of linking in Section 3 to provide stylized facts as well as Sections 4 and 5 to calculate the COLI. For the robustness check, we use another method by linking products only when successor and predecessor products are produced by the same manufacturer firm. 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.

Figure 3 provides another illustration of the use of the JAN code. In the graph, 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 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 the Japanese love for 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.

3.1 Product Turnover

Stylized Fact 1:
The product turnover rate is 30% 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 graph 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. 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 Appendix A explains details. The annual entry and exit rates generally fluctuate in a range between $25 - 35\%$, 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.[5]

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 and find that the rates of product entry and exit are both 25% per year. We also calculate creation and destruction rates, that is, the weighted analogues of the entry and exit rates, and show them in Table 2, which is comparable to their table 3. 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. 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

[5]In the graph, shaded areas represent Japan's recession periods. It appears that the entry rate drops during recessions, while the exit rate jumps up, implying the procyclicality of product turnover. In the Online Appendix, we confirm such procyclicality by regressing product turnover rates with sales growth at the 3-digit code product level.

destruction rates in Japan are around 40% per year, while they are less than 10% 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 reveal that almost 85% (65%) of products are not in the market nine (four) years later, which is again higher than the corresponding US figure of around 75% (50%).

Because there exists enormous heterogeneity in product turnover across products, we next compare product turnover between Japan and the United States at the product category level.[6] Figure 5 shows very clearly that product turnover rates are higher in Japan than in the United States for all product categories. It also shows that they are positively correlated each other with the Spearman rank-order correlation of 0.415, suggesting that products with a high turnover rate in the United States tend to have a high turnover rate also in Japan.

3.2 Price Changes Associated with Product Turnover

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 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 code product, 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 to two: contribution from sample rotations (turnover, i.e. (1)+(2)) and that from within rotations (matched sample, (3)). Note that, because the number

[6]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.

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 unit-price inflation is positive, although it is only 0.25% per year. This stems from two competing forces: price changes at sample rotations are positive, while price changes within rotations are negative. The former force dominates 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 theses 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% 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%. 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 12.6% 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 3%, 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.[7]

What factors are responsible for this price pattern, in particular, the recovery of the decline in the price of predecessor products by successor products or the stickiness of rebirth prices. 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 question can be addressed 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 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 $\ln q(t_b) - \ln q(t'_d)$

[7] Although we link products at the 3-digit code product, we admit that products can vary massively in their quality even within the same 3-digit code product. 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 manufacturer firm*. However, predecessor and successor products are not necessarily in the same 3-digit code product. We did so to ensure a sufficient number of samples. We found that the pattern was very similar to that in Figure 6. See the Online Appendix for the graph.

show that the quantity of new products purchased at entry is about $e^{0.447} - 1 \sim 56\%$ 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 -0.502, suggesting that over the life span of a product the quantity purchased declines by about 39%. 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. An immediate question is how persistent the demand increases at entry are. 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 group. 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 $e^{-0.4} - 1 \sim -30\%$ 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% 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 presene 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

In this section, we introduce a model to calculate the COLI, a welfare-based price 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.[8] 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 $i \in I_t$:[9]

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

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 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 need to 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

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

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

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.[10]

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.

4.1 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

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

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):

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

[10] 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.

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

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

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.

In sum, this equation illustrates that, as long as we know the sales shares of both newly entering and old exiting products, we can compute the rate of change in the COLI, without knowing the quality parameter b. This is the novel method developed by Feenstra (1994).

4.2 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.

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.

4.2.1 Special Case

As a special case, suppose

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

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.

4.2.2 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:

$$\ln\left(\frac{\sum_{i \in I_{t-1} \cap I_t} c_i(t)}{\sum_{i \in I_{t-1} \cap I_t} c_i(t-1)}\right) = \ln\left(\frac{\widetilde{p(t)^*}}{\widetilde{p(t-1)^*}}\right) + \frac{1}{1-\sigma}\ln\left(\frac{\widetilde{s(t)^*}}{\widetilde{s(t-1)^*}}\right) - \ln\left(\frac{\widetilde{\varphi(t)^*}}{\widetilde{\varphi(t-1)^*}}\right), \tag{8}$$

where the geometric average $\widetilde{x(t)^*} \equiv \left(\Pi_{i \in I_{t-1} \cap I_t} x_i(t)\right)^{1/N_{t,t-1}}$ and $N_{t,t-1}$ indicates 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,

$$\ln\left(\frac{\widetilde{\varphi(t)^*}}{\widetilde{\varphi(t-1)^*}}\right) = 0. \tag{9}$$

Note that the first and second terms in the right-hand side of equation (8) 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 (9). 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 but not necessarily so with the assumption adopted by Redding and Weinstein (2016).

4.2.3 Effect of Consumer Learning

In our model, we assume that consumers perfectly know their preferences about all available products, which is also the case in Feenstra (1994) and Redding and Weinstein (2016). However, in reality, consumers may well not know the quality or fashion effects of products until they purchase and test them. For the reason, high and transitory demand at entry may reflect that consumers try out new products to test their quality. Conceptually, our COLI is interpreted as the *ex ante* COLI, opposed to the *ex post* COLI that is based on realized preferences after consumers purchase products. Consumers decide their shopping given their prior belief about the quality and fashion effects of each product. Because consumers must purchase products before consuming, the *ex ante* COLI reflects their revealed preference.

With the learning effect, a market share of some products may increase over the

lifetime of the product, if it turns out to have better quality than consumers expected before they purchased. Our model can incorporate this effect as a negative fashion effect, because we specify neither the magnitude of the fashion effect nor its change. If the fashion parameter $\phi_i(t_i)$ starts from below one and converges to one, it indicates a negative fashion effect such that consumers appreciate the quality of a product more and more as time passes.

4.2.4 Effect of Selection

The COLI in our model is hardly influenced by firms' endogenous selection of products. It is true that manufacturers decide the timings of entry and exit endogenously. In particular, manufacturers are more likely to discard lower market share goods. On the other hand, in the calculation of the COLI, we use a partial-equilibrium model, taking firms' behaviors as given. In this respect, we assume an exogenous exit rate of products. However, each consumer is too small to influence manufacturers' decisions. Thus, even if manufacturers endogenously decide the timing of exit by looking at their sales shares, such a decision is still exogenous from the perspective of consumers. Thus, endogenous product exits do not cause a bias in our COLI. Furthermore, mathematically speaking, endogenous exits influence the COLI through the third term in equations (4) in the Feenstra (1994) model and (7) in our model, which represents one minus the fraction of products that exit in period t. If manufacturers are more likely to discard lower market share goods, the fraction of products that exit becomes close to zero and thus, the third term converges to one. Therefore, the endogeneity of product exits makes product exits matter less for the computation of the COLI. If firms decide to exit their product from the market within τ periods owing to low sales, we exclude its contribution to the COLI from our computations. However, because its sales are small, we can safely neglect their contribution, too.

4.3 Estimating 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 variables, so that we develop a method to estimate them by extending Feenstra (1994).

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 disappears after a while following a product's entry, the difference in the sales shares provides an indication of differences in their quality, provided we properly take a number of other factors into account.

We identify 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.

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

$$\frac{b_i}{b_{i'}} = \left[\frac{\frac{p_i(t_b+\tau)q_i(t_b+\tau)}{\sum_{j \in I_{t'_b} \cap I_{t_b+\tau}} p_j(t_b+\tau)q_j(t_b+\tau)}}{\frac{p_{i'}(t'_b+\tau)q_{i'}(t'_b+\tau)}{\sum_{j \in I_{t'_b} \cap I_{t_b+\tau}} p_j(t'_b+\tau)q_j(t'_b+\tau)}} \right] \left[\frac{p_{i'}(t'_b+\tau)}{p_i(t_b+\tau)} \right]^{1-\sigma} \left[\frac{\sum_{j \in I_{t'_b} \cap I_{t_b+\tau}} c_j(t_b+\tau)}{\sum_{j \in I_{t'_b} \cap I_{t_b+\tau}} c_j(t'_b+\tau)} \right]. \tag{10}$$

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'.

Fashion Effect

Next, we estimate the rate of change in the fashion effect. Again, we limit products' life span to τ or longer when estimating fashion effects. 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 $c_{i'}(t'_b) = b_{i'}\phi_{i'}(0)\left[p_{i'}(t'_b)\right]^{1-\sigma}$. Employing the same method as above yields

$$\frac{b_i\phi_i(0)}{b_{i'}\phi_{i'}(0)} = \left[\frac{\frac{p_i(t_b)q_i(t_b)}{\sum_{j \in I_{t'_b-\tau} \cap I_{t_b}} p_j(t_b)q_j(t_b)}}{\frac{p_{i'}(t'_b)q_{i'}(t'_b)}{\sum_{j \in I_{t'_b-\tau} \cap I_{t_b}} p_j(t'_b)q_j(t'_b)}} \right] \left[\frac{p_{i'}(t'_b)}{p_i(t_b)} \right]^{1-\sigma} \left[\frac{\sum_{j \in I_{t'_b-\tau} \cap I_{t_b}} c_j(t_b)}{\sum_{j \in I_{t'_b-\tau} \cap I_{t_b}} c_j(t'_b)} \right]. \tag{11}$$

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:

$$\phi_i(0) = \left[\frac{\frac{p_i(t_b)q_i(t_b)}{\sum_{j \in I_{t_b-\tau} \cap t_b+\tau} p_j(t_b)q_j(t_b)}}{\frac{p_i(t_b+\tau)q_i(t_b+\tau)}{\sum_{j \in I_{t_b-\tau} \cap I_{t_b+\tau}} p_j(t_b+\tau)q_j(t_b+\tau)}} \right] \left[\frac{p_i(t_b+\tau)}{p_i(t_b)} \right]^{1-\sigma} \left[\frac{\sum_{j \in I_{t_b-\tau} \cap I_{t_b+\tau}} c_j(t_b)}{\sum_{j \in I_{t_b-\tau} \cap I_{t_b+\tau}} c_j(t_b+\tau)} \right]. \tag{12}$$

5 Applying the Model to Japan

In this section, we apply the above model to Japan. We start by calculating time-series changes in the COLI at a monthly frequency. Next, we examine the size of quality and fashion effects.

We employ the following parameters. We set the elasticity of substitution σ to 11.5 based on Broda and Weinstein's (2010) estimate, although they mention that the demand elasticity typically lies between 4 and 7. As for the duration of the fashion effect τ, we set a value of 7 based on the bottom panel of Figure 7. We discuss how using different values for σ and τ changes the COLI below.

5.1 Price Index

5.1.1 Benchmark Result

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 of the matched sample that corresponds to the second term of equation (7) and is caculated by the Sato-Vartia method. While not shown in the figure to avoid it getting too cluttered, the inflation rate of 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% 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% points.

5.1.2 Comparison

In Table 4, we compare the COLI in our model with five different price indexes: the CPI, the matched sample, the 12-month matched sample, the COLI based on Feenstra's method, and the COLI based on Redding and Weinstein's method. The official CPI consists of processed food and domestic articles to match the coverage of our scanner data. As stated above, the inflation rate of the matched sample corresponds to the second term of equation (7) for the common set of $I_{t-\tau-1} \cap I_{t-1} \cap I_t$. In a similar way, we compute the inflation rate of the 12-month matched sample. This computation is also easy and straightforward, because we just compare price changes for the products that exist in the market at least for 12 months and apply the Sato-Vartia method. Moreover, because this index excludes products whose life spans are shorter than 12 months, it is not influenced by fashion effects. We also calculate the COLI based on Redding and Weinstein (2016) as well as Feenstra (1994).

The table shows that the change in the COLI in our model is -1.2% for its time-series mean and 1.8% for its standard deviation. The time-series means of price changes are high from the descending order of the CPI, the 12-month matched sample, our COLI, the matched sample, the COLI based on Feenstra's method, and the COLI based on Redding and Weinstein's method. As for the CPI, the dotted line in Figure 9 shows its change from the same month in the previous year. The CPI inflation rate often moves apart from the change in the COLI particularly in the 1990s. On average, the official CPI overestimates the inflation rate by about 1% point, if our COLI is correct. On the other hand, the COLI change based on Feenstra's method is massively lower, by about 10% points, than our COLI change. The COLI change based on Redding and Weinstein's method is even lower.

Comparing the inflation rate suggested by our model and that by the (12-month)

matched sample suggests that the latter is a good approximation of the COLI. As Figure 9 shows, the COLI moves in tandem with the inflation rate of the matched sample. In other words, the quality and fashion effects on the COLI are almost equal in size to those of firms' efforts to recover the price decline at entry. On average, the COLI change is by 1% point higher than the inflation rate of the matched sample, suggesting that the downward effects of quality and fashion on the COLI are smaller than the upward effect of firms' price recovery efforts. A difference from the COLI change is even smaller for the inflation rate of the 12-month matched sample. In this respect, the 12-month matched sample is a good approximation to the COLI, although it takes account of neither quality nor fashion effects.

5.1.3 Robustness Check

We next examine the robustness of our results to different specifications. We first consider how the choice of the duration of the fashion effet, τ, influences our results. In Figure 10 we plot the inflation rates of the matched sample and the COLI using lower values for τ in addition to 7, namely, 0, 1, and 4. The case for $\tau = 0$ corresponds to Feenstra's method. We find that as τ increases, the inflation rate of the matched sample slightly increases. 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, which increases the inflation rate of the matched sample. The COLI also increases as τ increases. Most notably, for the short life span of $\tau = 0$ and 1, the inflation rate of the COLI is below that of the matched sample, unlike in the other two cases. Because in this case a demand increase that lasts for more than zero or one month is regarded as a quality change rather than the result of the fashion effect, the COLI decreases considerably. On the other hand, as τ increases, the inflation rate of the COLI increases, but the results using $\tau = 4$ and 7 are very similar. In other words, most of the difference in the COLI between Feenstra's model and ours is captured even with small $\tau = 4$.

In the aforementioned Table 4, we report the COLIs under different specifications. The twice increase in τ from 7 to 14 hardly changes the COLI. When we use a lower value of $\sigma = 4$ or 8 than 11.5, we find that the COLI inflation rate increases and diverges from the inflation rate of the matched sample. For $\sigma = 4$, the average change in the COLI increases from -1.2% to 1.3%. However, the sensitivity of the COLI inflation rate to σ is quantitatively smaller than that in Feenstra's (1994) COLI inflation rate. This is

because the discrepancy of the inflation rate between the COLI and the matched sample is smaller in our model. Even for $\sigma = 11.5$, a big gap exists between the COLI and the matched sample in Feenstra's method. A lower σ magnifies this gap, yielding -28.4% inflation rate on average for $\sigma = 4$.

Next, we calculate the COLI by allowing retailer firms to change over time. So far we have limited our analysis to 14 retailers that exist throughout the observation period. Although this was intended to isolate the true effects of product turnover by excluding the effects of the increase in retailers, it leads to a smaller sample size. Furthermore, the isolation may be possible even for time-varying retailers by restricting to the JAN code products that are available at more than two retailers. The second row from the bottom in the table shows that the COLI inflation rate changes by less than 1% 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 resolve this problem, 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 the table shows that this changes the COLI by less than 1% point.

5.2 Quality and Fashion Effects

Using the method outlined in Section 4.3, we compute the size of the quality and fashion effects for Japan. To do so, we link product predecessors and successors at the 3-digit code (product category) level as explained in Section 2. It is not necessary to link predecessors and successors for each product, as we discuss in Appendix C. We estimate the size of the quality and fashion effects at the 3-digit code product level for each month. We then calculate the median, rather than the mean, because we notice that the estimates of quality and fashion effects entail high volatility and measurement errors, stemming from the fact that the sales share as well as prices of entering and exiting products are highly volatile. The results are shown in Figures 11 and 12.

5.2.1 Quality Effect

The upper panel of Figure 11 shows the density function of the rate of change in quality estimated from equation (10), which is calculated as the time-series median of quality changes at each 3-digit code product. The horizontal axis represents $b_i/b_{i'}$, where a value above one represents 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 remained more or less unchanged at entry. Because the distribution is skewed to the right, some products seem to have experienced significant quality improvements, while other products experienced a moderate quality deterioration.

The lower panel shows the rate of aggregated quality changes over time, which is aggregated by taking the median of the quality changes over all 3-digit code products for each year.[11] On average, it exceeds one, but it declined over the two decades from about 2 to 1. This, together with the findings obtained earlier, suggests that as the number of products introduced into the market increased, the improvement in quality with each new product declined. The decline in the rate of change in quality has resulted in upward pressure on the rate of change in the COLI.

5.2.2 Fashion Effect

Next, the upper panel of Figure 12 shows the density function of the fashion effect estimated from equation (12), which is calculated as the time-series median of the fashion effect at each 3-digit code product. The distribution of $\phi_i(0)$ has the mode around two. The middle panel shows developments in the fashion effect, which is aggregated by taking the median over all 3-digit code products for each year. Both the upper and middle panels show that the estimated $\phi_i(0)$ exceeds one, suggesting considerable fashion effects. Moreover, the level of the fashion effects keeps increasing during the observation period. Finally, the lower panel shows developments in the rate of change in the fashion effect, $\phi_i(0)/\phi_{i'}(0)$, over time computed from equation (11). The graph shows that the rate of change has been stable over time, slightly higher than one.

The increase in the fashion effects is consistent with the increasing popularity of "limited" products that we showed in Figure 8. While our analysis cannot tell us whether the

[11]Note that, in this time-series graph, the birth year of predecessors, t'_b, is not fixed, although the birth year of successors, t_b, coincides with the year in the horizontal axis. Thus, it does not show the rate of change in quality per year, but per product turnover.

reason for the increase in "limited" products is that consumers' taste for such products increased or, alternatively, firms realized that there was latent demand for such products and they responded by offering more of such products, the increased offering of such products appears to be an important strategy by firms to raise sales under deflation.

5.2.3 Discussions

It is important to examine whether we are truly identifying the quality and fashion effects. To this end, we do mainly three things. First, we compare our results with those in Feenstra (1994), because our model is essentially the same as Feenstra (1994). In particular, regarding the quality effect, our model should not be far from Feenstra (1994). Figure 13 confirms this. To draw the graph, we first calculate quality parameter $b_i/b_{i'}$ between the Feenstra (1994) model and our model with various $\tau = 1,\ 4$, and 7 for each 3-digit code product for each month. We then calculate the correlations between two monthly series of $b_i/b_{i'}$ for each 3-digit code product and show their histogram in the figure. Because two models differ only in the incorporation of the fashion effect, their correlations are close to one. The lower duration of the fashion effect, τ, in our model, the more likely the fashion effect is to be interpreted as the quality effect. Thus, as τ decreases, $b_i/b_{i'}$ in our model becomes closer to that in Feenstra (1994) and the correlation increases to one. They perfectly coincide when $\tau = 0$.

The second thing we do is a comparison of estimated quality growth and fashion effects, that is, $b_i/b_{i'}$ and $\phi_i(0)$, with various kinds of variables at a 3-digit code product level. The variables we use are the gross creation rate (the sum of creation and destruction rates), the net creation rate (creation minus destruction), the growth rate of sales, the Herfindahl-Hirschman Index (HHI), the price variance, and the shopping frequency. All the variables except for the last one are the mean of their monthly series and taken from the same scanner data. The price variance represents the variance of posted prices in each 3-digit code product. The data on the shopping frequency are those in 2013 at a product category and obtained from Statistical Bureau "Family Income and Expenditure Survey" in 2013 that asks about 8,000 households with two or more family members regarding how frequent they go shopping in a year.

We choose these variables because we expect to see the following relations. First, quality growth is high for the 3-digit code product that experiences high growth in terms of its number of products and/or sales. Thus, the net creation rate and the growth rate of

sales are likely to be positively correlated with quality growth. Second, the fashion effect is high for the 3-digit code product with a high turnover rate (gross and net creation rate). This is because manufacturer firms can exploit the fashion effect and increase their profits by frequent product changes. Third, in a 3-digit code product with a high fashion effect, the HHI is low. This is because it is difficult for manufacturer firms to monopolize the market in such a product category, because new products continuously enter the market to attract customers by the fashion effect. Fourth, the price variance is high in a 3-digit code product with high quality growth or a high fashion effect. It is natural to consider that prices are proportional to quality and fashion effects. This is particularly so, for example in the quality ladder model, in a flexible-price environment. Thus, if there is an improvement in quality from existing products or a fashion effect, then its price is considered to be higher than from those of existing products, which increases the price variance in the 3-digit code product. Finally, quality growth has a negative relation with the shopping frequency, if infrequently purchased products are associated with high durability and high durability is associated with high quality growth.[12]

Table 5 shows the Spearman rank-order correlations, where figures in parentheses indicate p-values.[13] We calculate the correlations for 186 3-digit code products out of 214, which enables us to obtain $b_i/b_{i'}$ and $\phi_i(0)$ for at least 20 months in 25 years (300 months). Figure 14 shows two scatter plots for an illustrative purpose. The results in the table and figure are mostly consistent with our predictions. Products with high quality growth are positively correlated with those with high growth in sales, high net creation, and high price variance, while they are negatively correlated with the shopping frequency. Products with high fashion effects are positively correlated with those with high gross and net creation rates and high price variance and negatively correlated with those with the low HHI, although they are also correlated positively with growth in sales.

Third, we measure quality growth, $b_i/b_{i'}$, for the products that change only their size (e.g., weight or pieces in a bag) at turnover, while the other characteristics such as

[12]Notable examples are TVs and automobiles. However, such electric items or automobiles are not included in our dataset. The relation between the fashion effect and the shopping frequency can be both positive and negative. It can be negative if consumers love to purchase new products simply because they purchase them infrequently. The relation can be positive if products with high fashion effects induce consumers to shop frequently to search for new products.

[13]We calculate the Spearman rank-order correlations rather than simple correlations, because the former is robust to outliers.

their brand name and manufacturer are unchanged. At this type of turnover, we expect to see a positive correlation between a size change and quality growth. To this end, we borrow the work by Imai and Watanabe (2014) who identify 10,000 cases of such product turnover from product labels. A challenge in this measurement is that there are few number of pairs of products that change only their size, because the timing of a predecessor's exit rarely coincides with the timing of a successor's entry. We thus pin down only 209 cases out of 10,000 to estimate quality growth.[14] The Spearman rank-order correlation between product size change and quality growth turns out to be 0.204, with the p-value of 0.003, which is consistent with our prediction.

6 Concluding Remarks

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 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

[14]Moreover, consumers can purchase other products if they do not like them. For these reasons, this grouping is not applicable to the computation of the COLI.

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) Except when calculating the COLI, 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.

   (b) To construct the COLI, we use the formula explained in the main text for products in each 3-digit category. We then aggregate the COLI at the 3-digit category level using the sales weight.

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 (10):

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

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	-0.087	-0.507
From death predecessor to birth successor	0.126	0.480
From birth predecessor to birth successor	0.038	-0.027

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: Spearman Rank-order Correlations at the 3-digit Code Product Level

	$b_i/b_{i'}$	$\phi_i(0)$
Creation + destruction rate	-0.011 (0.878)	0.377*** (1.470e-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*** (4.96e-05)
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.

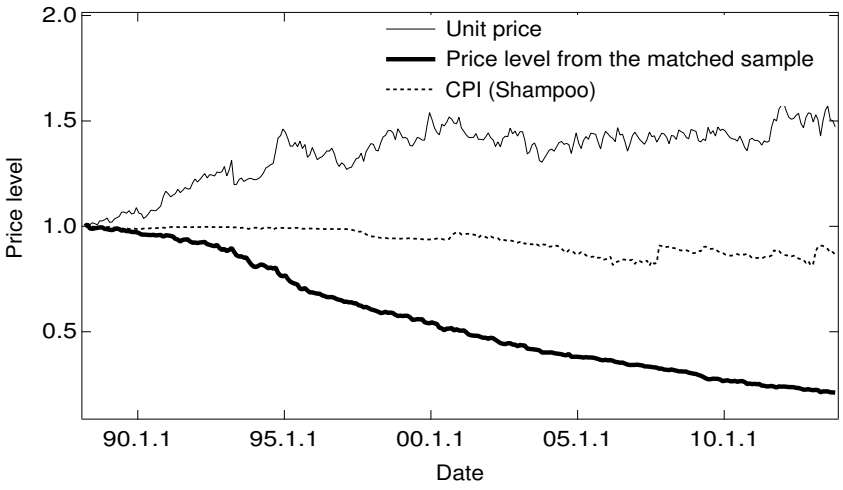


Figure 1: Prices of Shampoos

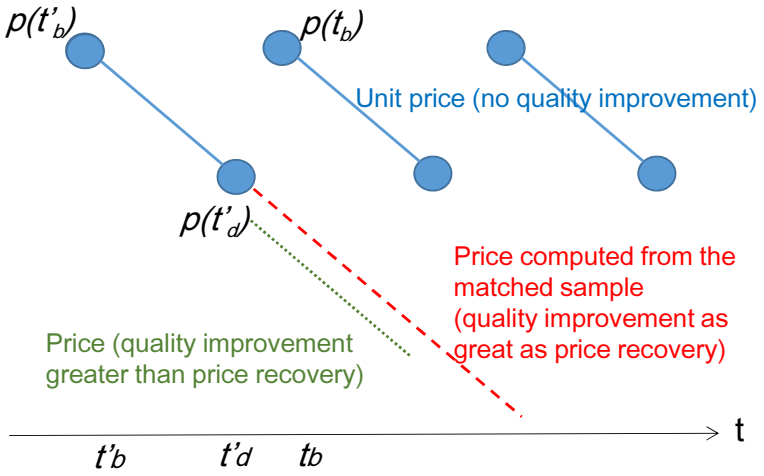


Figure 2: Pattern of Price Changes and Price Indexes

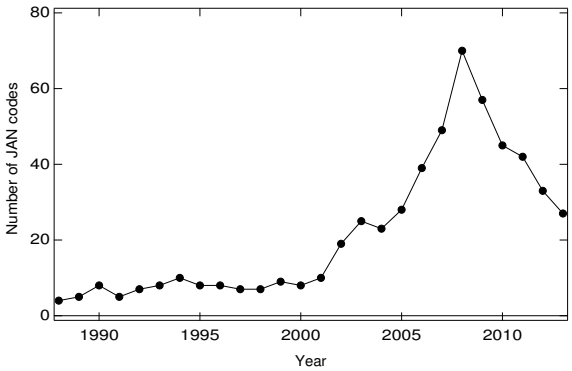


Figure 3: Number of "Kit Kat" Products

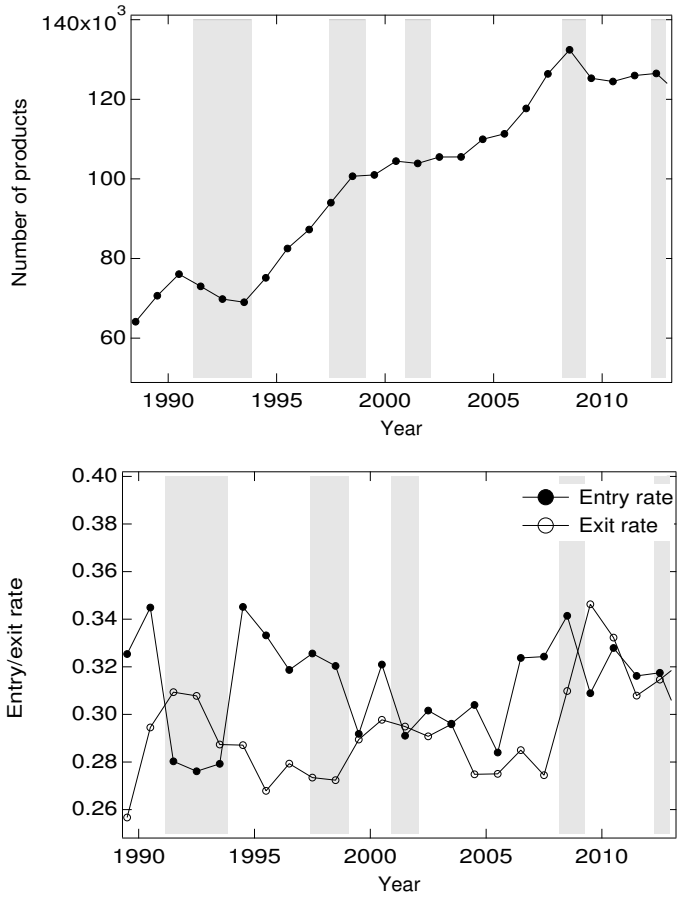


Figure 4: Number of Products (top) and Entry and Exit Rates (bottom)

Note: Shaded areas represent Japan's recession periods.

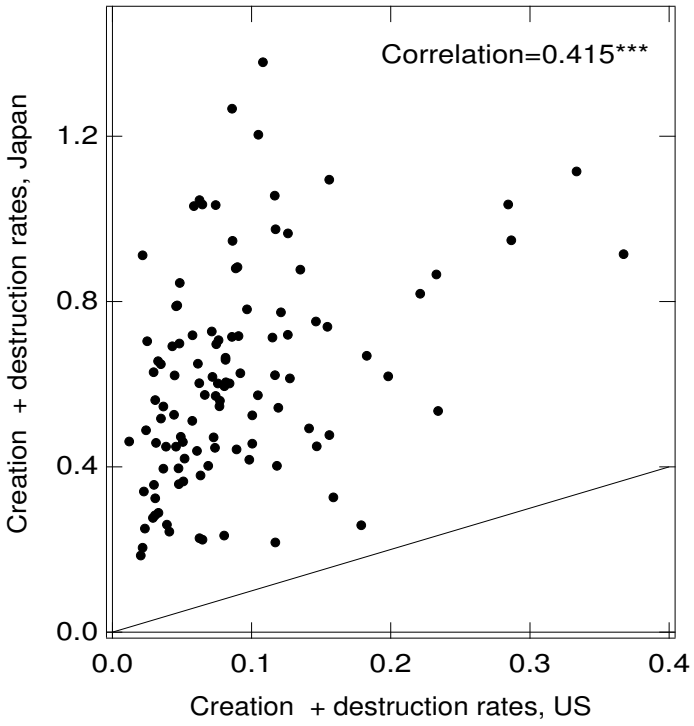


Figure 5: Comparison of Creation and Destruction Rates between US and Japan

Note: Each dot represents Japan's 3-digit code product. 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.

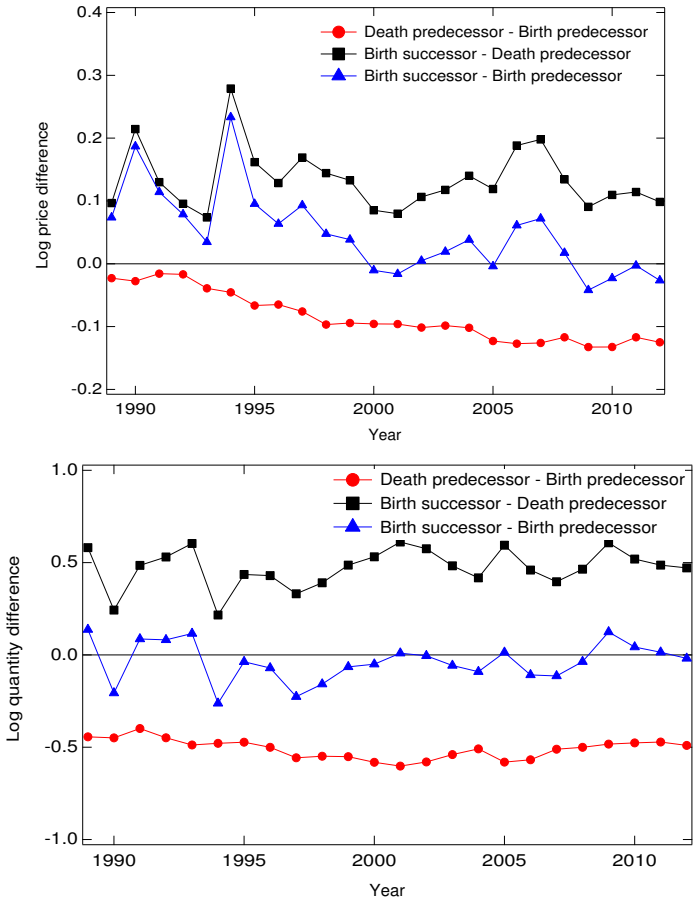


Figure 6: Price and Quantity Changes over the Product Cycle

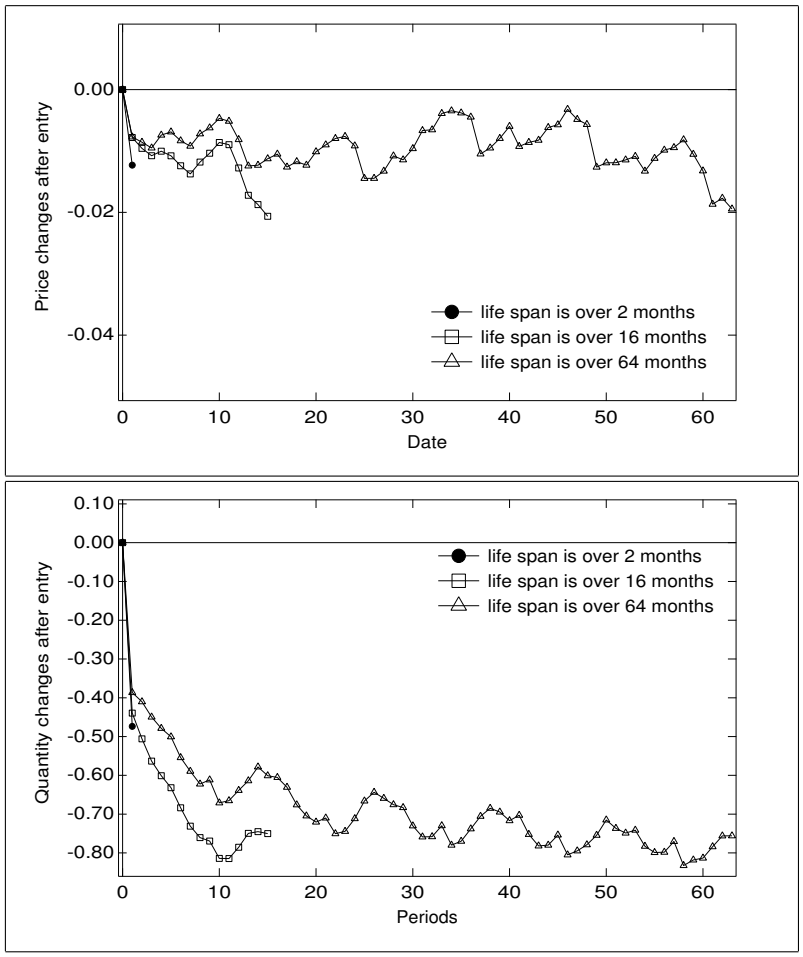


Figure 7: Price and Quantity Changes after Entry

Note: The horizontal axis represents the number of months since products were 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.

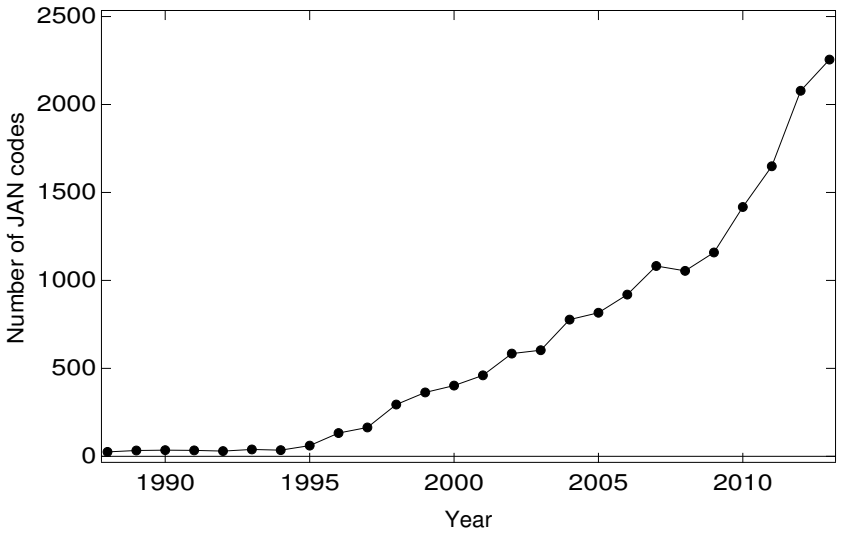


Figure 8: Number of "Limited" Products

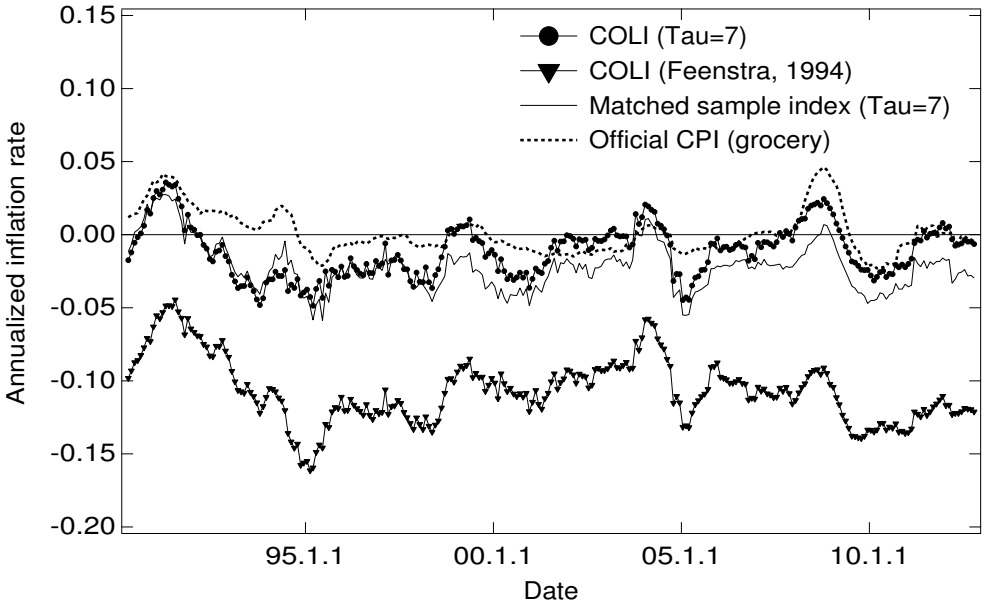


Figure 9: The Cost-of-Living Index (COLI)

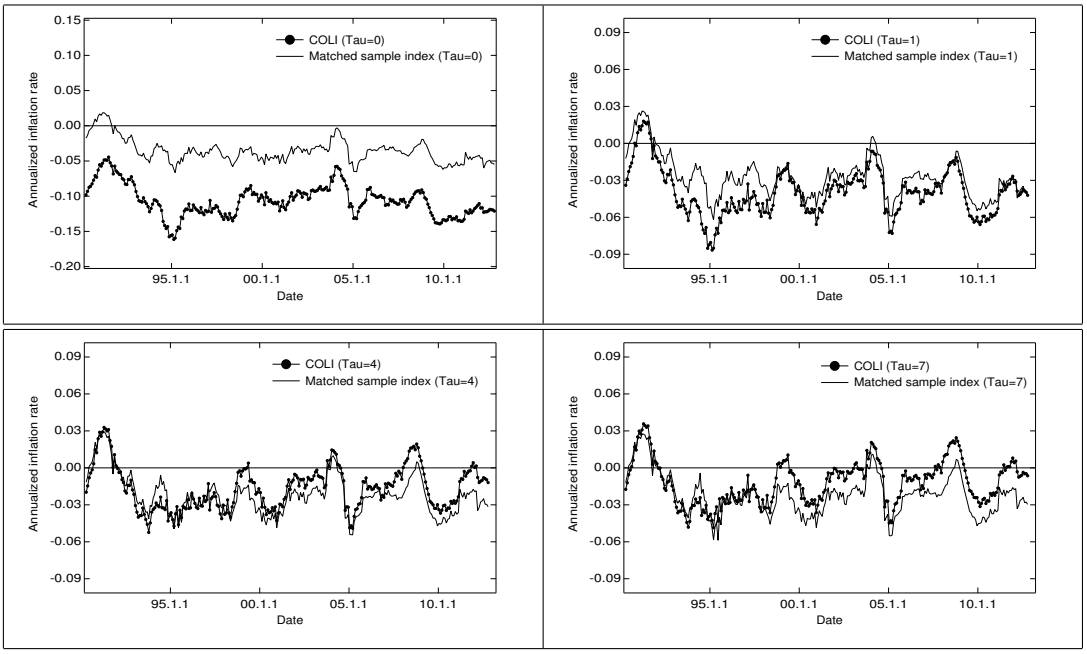


Figure 10: The COLI Under Different τ

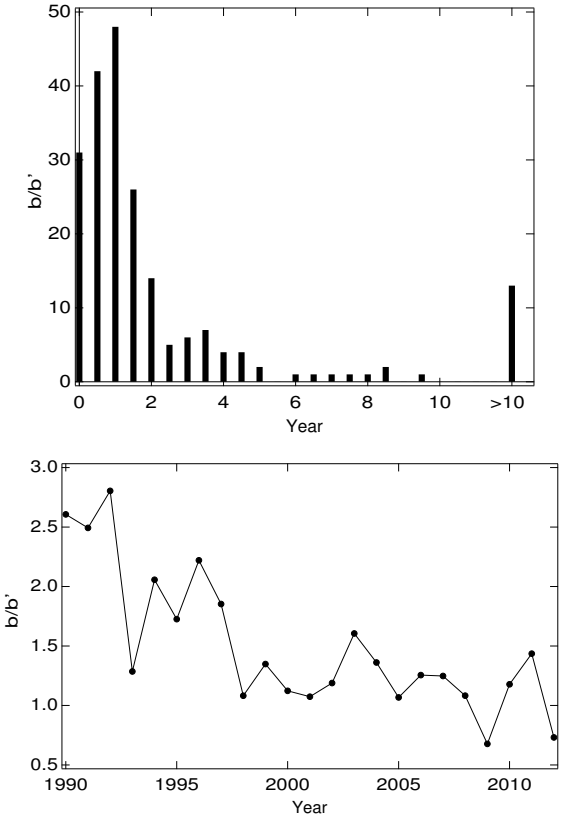


Figure 11: Quality Effect

Note: The upper panel shows the density function of changes in quality, while the lower panel shows developments in quality changes over time.

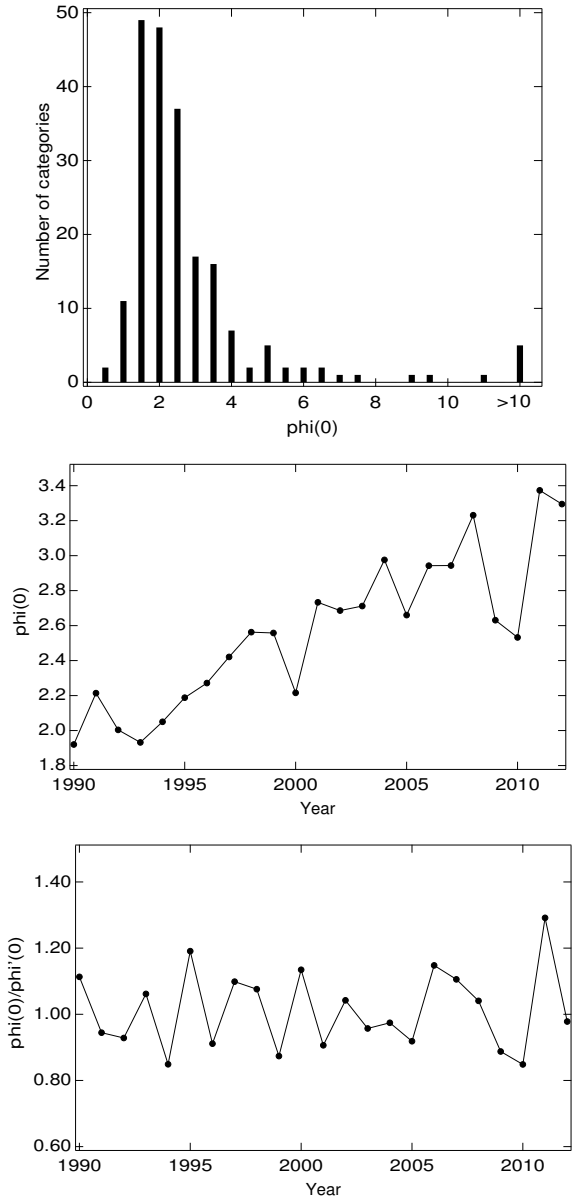


Figure 12: Fashion Effect

Note: The upper panel shows the density function of the fashion effect, while the middle panel shows developments over time. The lower panel shows developments in the rate of change in the fashion effect.

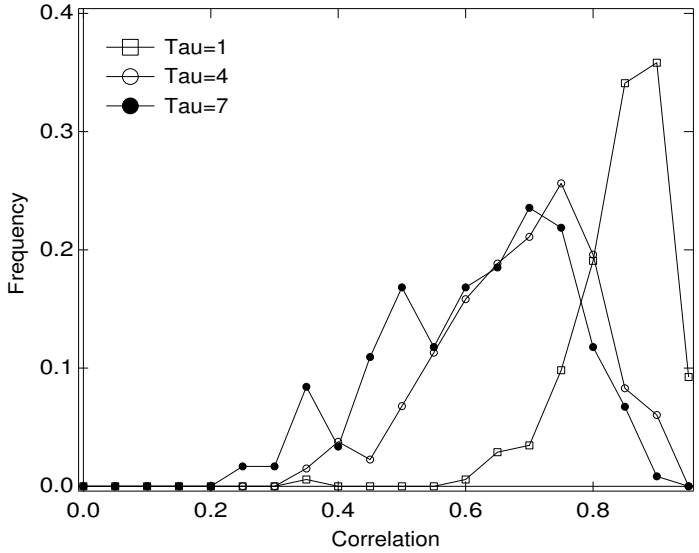


Figure 13: Histogram of the Correlations of the Quality Effects between Feenstra's (1994) Method and Ours

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 code product and then show their histogram.

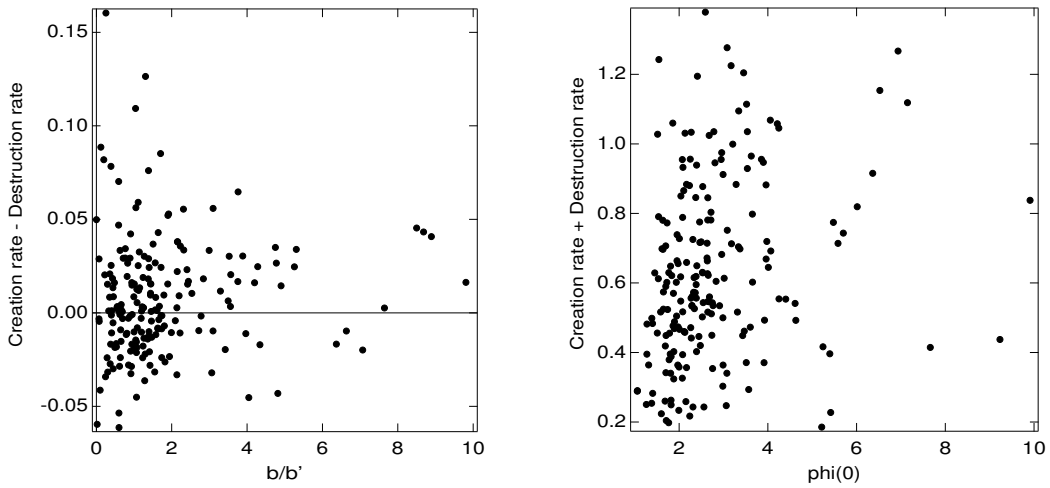


Figure 14: Estimated Quality Growth and Fashion Effects by 3-digit Code Products

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 code product.