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Estimating Daily Inflation Using Scanner Data: A Progress Report

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Abstract

We construct a Törnqvist daily price index using Japanese point of sale (POS) scanner data spanning from 1988 to 2013. We find the following. First, the POS based inflation rate tends to be about 0.5 percentage points lower than the CPI inflation rate, although the difference between the two varies over time. Second, the difference between the two measures is greatest from 1992 to 1994, when, following the burst of bubble economy in 1991, the POS inflation rate drops rapidly and turns negative in June 1992, while the CPI inflation rate remains positive until summer 1994. Third, the standard deviation of daily POS inflation is 1.1 percent compared to a standard deviation for the monthly change in the CPI of 0.2 percent, indicating that daily POS inflation is much more volatile, mainly due to frequent switching between regular and sale prices. We show that the volatility in daily inflation can be reduced by more than 2daily inflation rate 0 percent by trimming the tails of product-level price change distributions. Finally, if we measure price changes from one day to the next and construct a chained Törnqvist index, a strong chain drift arises so that the chained price index falls to 10^{-10} of the base value over the 25-year sample period, which is equivalent to an annual deflation rate of 60 percent. We provide evidence suggesting that one source of the chain drift is fluctuations in sales quantity before, during, and after a sale period.

JEL Classification Number: E31; C43
Keywords: scanner data; consumer price index; Törnqvist index; chain drift; trimmed means; regular and sale prices; deflation

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1 Introduction

Japan's central bank and government are currently engaged in a major experiment to raise the rate of inflation to the target of 2 percent set by the Bank of Japan (BOJ). With overcoming deflation being a key policy priority, a first step in this direction is the accurate assessment of price developments. In Japan, prices are measured by the Statistics Bureau, Ministry of Internal Affairs and Communications, and the consumer price index (CPI) published by the Statistics Bureau is the most important indicator that the BOJ pays attention to when making policy decisions. The CPI, moreover, is of direct relevance to people's lives as, for example, public pension benefits are linked to the rate of inflation as measured by the CPI.

However, measuring prices is by no means a straightforward matter. For example, individual consumers may start purchasing slightly cheaper goods at a slightly cheaper shop than before, and if, as in Japan during the long-term economic stagnation, such a pattern takes hold, it may have a profound effect on the rate of inflation. Yet, accurately tracking this kind of behavior by consumers is difficult. Given the government's budget constraints, the Statistics Bureau has only a limited number of price collectors and cannot possibly monitor the purchasing behavior of all consumers. The best the Statistics Bureau can do is to collect prices at retailers and for products decided on in advance.

In order to address such problems associated with constructing price indexes in the traditional manner, efforts are underway in a number of European countries, such as Switzerland, Norway, and the Netherlands, to construct consumer price indexes using scanner data, that is, data that are collected when the barcode of a product is read at the check-out of a retailer such as a supermarket. Statistical agencies in these countries obtain such data with the cooperation of retailers and construct price indexes using these data. The scanner data make it possible to trace if consumers chased after slightly cheaper goods, to reliably capture items registering high sales volumes, and to measure price indexes with great accuracy. Opportunities to use scanner data for research on prices are also growing rapidly, and since Feenstra and Shapiro (2003), various studies have been conducted. The pioneering study for Japan is Ariga, Matsui and Watanabe (2001), while more recent studies include Abe and Tonogi (2010), Ariga and Matsui (2003), Matsuoka (2010), Imai, Shimizu and Watanabe (2012), Imai and Watanabe (2014), and Sudo, Ueda and Watanabe (2014).

The aim of this paper is to measure a daily price index using scanner data. The source data used are the scanner data provided by Nikkei Digital Media, Inc. (referred to as "Nikkei data" below). Covering about 300 supermarkets throughout Japan, the data comprise all the items sold by these supermarkets (food, daily necessities, etc.). There are more than 200,000 products. The most important feature of the Nikkei data, for our purposes, is that they contain daily sales records spanning the quarter of a century from 1988 to 2013. While there are many scanner datasets in the world, none cover a period as long as this.

To construct a price index that closely reflects actual consumption patterns, what is important is to obtain accurate information on what products are selling well and to aggregate prices based on this information. Statistical agencies in all countries, including Japan, conduct surveys every few years to collect this information. However, these days, with fierce price competition among firms, which products sell well changes almost on a daily basis, so that such surveys are of limited usefulness. In contrast, the scanner data we use for constructing our daily price index contain records not only of the sales prices but also of sales quantities, allowing us to accurately grasp which products are selling well. Specifically, we calculate the rate of price change for each individual good and construct a weighted price index using the sales shares of a particular product in the two periods being compared (for example, today and the same day one year ago), with weights being calculated by adding up these two shares and dividing by two.[1] Employing this approach, price changes of products that account for a large sales share also have a large impact on the price index. An index using this weighting method is called a Törnqvist index, and the literature on index construction suggests that it possesses a number of highly desirable characteristics (see, e.g., Diewert (1978)).

This paper is not the first attempt to measure a daily consumer price index. Other examples include the Billion Prices Project (`http://bpp.mit.edu/`) at the Massachusetts Institute of Technology (MIT), which has been gathering prices on the internet since 2010 to construct a daily price index. This index is widely used by financial institutions and investors for forecasting the CPI released by the US Bureau of Labor Statistics. A similar project was launched by Google in 2010, which crawls the internet to gather prices to construct a daily price index for the world as a whole. What these two projects have in common is that they crawl the internet for prices. However, a deep-seated criticism of the indexes by MIT and Google is that prices posted on the internet tend to differ from those charged by brick-and-mortar retailers, and even though shopping on the internet is growing, internet prices at present are not particularly representative. What is more, these projects do not gather information on sales quantities, so that it is not possible to use weighted averages that are in accordance with index theory. Against this background, the daily index constructed in this study is unique in that it uses prices gathered in real shops and takes into consideration changes in sales quantities.[2]

[1] In contrast, Laspeyres weights, for example, are calculated by using the sales share in the base period.

[2] The pioneering example of a daily price index is the consumer price index constructed since 2006 by the Fundação Getulio Vargas (FGV), a private think tank in Brazil (`http://portalibre.fgv.br/`). Although prices for this index are gathered in the traditional manner by price collectors, the index is updated every day. It is calculated using the fixed base Laspeyres method. The fact that it is Brazil that gave birth to the first daily price index reflects the country's experience with bouts of high inflation in the past and that since then people have been monitoring prices at a high frequency. For more details on the daily price index by the FGV, see Ardeo, Margarida and Picchetti (2013).

The rest of the paper is organized as follows. Section 2 provides an outline of the data used, while Section 3 explains the methodology to estimate the daily price index. Section 4 then reports the results. Specifically, Section 4.1 compares the daily and monthly price indexes constructed based on the scanner data as well as the scanner data monthly price index and the monthly consumer price index published by the Statistics Bureau. Section 4.2 shows results on the daily inflation rate by item. Next, Section 5 discusses some additional issues to make the daily index more reliable and useful. In particular, Section 5.1 discusses how to reduce the high volatility in the daily inflation rate and seeks to construct a core inflation measure. Further, Section 5.2 decomposes daily inflation fluctuations into those due to regular price changes and those due to changes in prices owing to sales. Section 5.3 then discusses issues related to chained indexes with special focus on the degree and the source of chain drift. Section 6 concludes the paper.

2 Data

The data we use for the construction of price indexes in this paper are the daily point of sale (POS) data collected by Nikkei. The observation period is March 1, 1988 to October 31, 2013, and the data provide daily sales records for products sold in around 300 supermarkets sampled from around Japan. The supermarkets include everything from hypermarkets to relatively small independent general merchandise stores. The dataset contains a total of about 1.8 million products over the entire sample period. The data comprises about 6 billion records, where one record consists of the quantity $q_{t,s,i}$ of good i sold on day t at supermarket s and the sales amount $e_{t,s,i}$. Most of the items for which such data are collected are processed food and daily necessities, and perishable food and durable goods, services, etc., are not included.

Each good i recorded is classified into a six-digit category (six digit number code; about 1,800 categories) and a superordinate three-digit category (three digit number code; about 200 categories). For example, Cup Noodles manufactured by Nissin Foods fall under the six-digit category "instant cup Chinese *soba*" (Chinese-style noodles), which in turn falls under the three-digit category "instant cup noodles," the latter of which also contains "instant cup *yakisoba*" (fried noodles), "instant cup Japanese *soba*" (Japanese-style noodles), "instant cup *udon*" (thick noodles), and "other instant cup noodles."

Moreover, each good has a 13-digit or eight-digit Japanese Article Number code (JAN code) allowing manufacturers and retailers to distinguish goods. In this paper, we follow this practice and use JAN codes to distinguish goods. However, one problem that arises is that the JAN codes for goods that are no longer being produced are reassigned to new goods, and in some cases old and new goods are in circulation simultaneously, so that there are different goods for one single JAN code. In the case that there is no one-to-one correspondence between a JAN code and a good, various different scenarios arise, and in order to deal with this issue, Nikkei attaches its own generation code (GEN code) when one JAN code corresponds to several goods. Thus, while we primarily rely on JAN codes in this study, we combine them with GEN codes where necessary to uniquely identify each good with a code.

Table A1 provides an overview of the POS data used in this paper. The number of retailers covered was well below 100 when the data collection started. However, it has grown considerably since and surpassed 100 in 1994 and 200 in 2007, and stood at 261 in the most recent full year (2012). The number of products (i.e., the number of JAN codes) handled by these stores in the early 1990s was about 130,000, but it has gradually increased over the years and in 2012 stood at more than 350,000. The increase in the number of products to some extent reflects the increase in the number of retailers covered. However, even when looking at the same retailers, the number of products has tended to rise, indicating that product variety has been increasing over the years. The sales of the retailers in the database in 2012 stood at ca. 400 billion yen, while the number of records in that year was about 450 million. For the sample period as a whole, the number of records used for the measurement of the price index is 5.8 billion. A list of the three-digit categories of the POS data is provided in Table A2.

3 Methodology

This section explains the methodology we employ for the calculation of the daily price index. Specifically, Section 3.1 presents the approach for constructing the price index using the POS data, while Section 3.2 explains the procedure for comparing the price index using the POS data with the price index by the Statistics Bureau.

3.1 Three-stage aggregation of price changes

Price indexes are calculated by aggregating the price changes of individual goods. Specifically, for the construction of our price index, the first step we take is to calculate the price of a good i by dividing the total sales amount at retailer s on day t by the total sales quantity. The price of that good is represented by $p_{t,s,i}$ ($p_{t,s,i} \equiv e_{t,s,i}/q_{t,s,i}$). Next, we compare the price of that good at time $t-dt$ and time t and calculate the rate of change. Finally, we aggregate step by step the price changes in the following manner: (1) Lower-level aggregation: For all goods belonging to three-digit category c sold by retailer s, we calculate the rate of price change from time $t - dt$ to time t and calculate the weighted average of that price change. We denote this price index for each retailer and three-digit category by $\pi_{t,c,s}$; (2) Mid-level aggregation: We calculate the weighted average of $\pi_{t,c,s}$ across retailers and denote the index for each three-digit category by $\pi_{t,c}$; (3) Upper-level aggregation: We calculate the weighted average of $\pi_{t,c}$ across three-digit categories to obtain the overall price index π_t. The details of the lower-level, mid-level, and top-level aggregation are as follows.

Construction of three-digit-level indexes by retailer Using the price information for each individual good i and defining the price change as the log difference between time $t - dt$ and time t, we calculate the weighted average of the price change for each retailer s and three-digit category c, i.e.:

$$\pi_{t,c,s} = \sum_{i \in I_{[t,t-dt],s,c}} \omega_{t,s,i} \ln \left(\frac{p_{t,s,i}}{p_{t-dt,s,i}} \right) \tag{1}$$

where $I_{[t,t-dt],s,c}$ is the set of goods in three-digit category c at retailer s at time $t - dt$ and time t. Goods sold at time t include some items that only started to be sold after $t - dt$, so that there are no sales records for them at time $t - dt$. Similarly, some of the goods sold at $t - dt$ were phased out before time t. Such goods for which there are no records at both points in time are not included in this set. As for the weight $\omega_{t,s,i}$ for each good i in equation (1), we calculate the sales share of good i in category c at time t and $t - dt$ at each retailer and define the average as follows:

$$\omega_{t,s,i} = \frac{1}{2} \left(\frac{e_{t-dt,s,i}}{\sum_{i \in I_{[t,t-dt],s,c}} e_{t-dt,s,i}} + \frac{e_{t,i,s}}{\sum_{i \in I_{[t,t-dt],s,c}} e_{t,s,i}} \right) \tag{2}$$

The above formula for calculating the weight, which uses the average of the sales shares at the two points in time, is called the Törnqvist formula, and the price index that we calculate in this paper using the weight shown in equation (2) is a Törnqvist index. In contrast, the consumer price index (CPI) published by the Statistics Bureau is based on Laspeyres weights, meaning that it uses only the consumption weight in the base period. Specifically, the weights used for the CPI are the expenditure amounts for each item (revised every five years) taken from the Family Income and Expenditure Survey (FIES) in the base period. However, in the aggregation for the CPI, the consumption weight is considered only in the upper-level aggregation, while in the lower-level aggregation – that is, in the process of aggregating individual prices to an item level price index – the unweighted arithmetic mean of prices collected from retailers is taken. This is called the Dutot formula.

Further, in equation (1), for ease of calculation we define the price change as the log difference between two points in time and takethe arithmetic mean of these price changes. On the other hand, the inflation rate is also frequently calculated as the geometric mean of price ratios. Although the two are approximately the same if price changes between the two points in time are sufficiently close to zero, i.e., $\ln(p_{t,s,i}) - \ln(p_{t-dt,s,i}) \approx \frac{p_{t,s,i} - p_{t-dt,s,i}}{p_{t-dt,s,i}}$, the larger the price changes are, the more the two diverge. For this reason, when discussing the inflation rate based on the POS data, we do not use the log price growth but the rate of price change by transforming π to $\exp(\pi) - 1$.

Construction of three-digit-level indexes Next, we calculate the rate of price change for each three-digit category by taking the weighted average across retailers of the $\pi_{t,s,c}$ measured in the previous step. Specifically, we calculate

$$\pi_{t,c} = \sum_{s \in S_{[t,t-dt]}} \omega_{t,s,c} \pi_{t,s,c} \tag{3}$$

where $S_{[t,t-dt]}$ is the set of retailers existing both at time $t - dt$ and time t. Moreover, $\omega_{t,s,c}$ is defined as follows:

$$\omega_{t,s,c} = \frac{1}{2} \left(\frac{\sum_{i \in I_{[t,t-dt],s,c}} e_{t-dt,s,i}}{\sum_{\substack{s \in S_{[t,t-dt]} \\ i \in I_{[t,t-dt],s,c}}} e_{t-dt,s,i}} + \frac{\sum_{i \in I_{[t,t-dt],s,c}} e_{t,s,i}}{\sum_{\substack{s \in S_{[t,t-dt]} \\ i \in I_{[t,t-dt],s,c}}} e_{t,s,i}} \right) \tag{4}$$

That is, weight $\omega_{t,s,c}$ is a weight based on the Törnqvist formula, which averages the sales shares at times $t - dt$ and t of goods categorized into three-digit category c and sold at retailer s, for which there were sales in both periods $t - dt$ and t.

Construction of the overall index Finally, taking the weighted average across three-digit categories of the $\pi_{t,c}$ measured in the previous step, we calculate the overall rate of price change by aggregating all the three-digit categories:

$$\pi_t = \sum_{c \in C_{[t,t-dt]}} \omega_{t,c} \pi_{t,c} \tag{5}$$

where $C_{[t,t-dt]}$ is the set of three-digit categories existing both at time $t - dt$ and time t. Moreover, $\omega_{t,c}$ is defined as the following Törnqvist weight:

$$\omega_{t,c} = \frac{1}{2} \left(\frac{\sum_{\substack{s \in S_{[t,t-dt]} \\ i \in I_{[t,t-dt],s,c}}} e_{t-dt,s,i}}{\sum_{\substack{c \in C_{[t,t-dt]} \\ s \in S_{[t,t-dt]} \\ i \in I_{[t,t-dt],s,c}}} e_{t-dt,s,i}} + \frac{\sum_{\substack{s \in S_{[t,t-dt]} \\ i \in I_{[t,t-dt],s,c}}} e_{t,s,i}}{\sum_{\substack{c \in C_{[t,t-dt]} \\ s \in S_{[t,t-dt]} \\ i \in I_{[t,t-dt],s,c}}} e_{t,s,i}} \right) \tag{6}$$

That is, $\omega_{t,c}$ is the average of the sales shares at times $t - dt$ and t of goods classified into three-digit categories c (for which there were sales in both periods $t - dt$ and t) aggregated over retailers.

The above three-step procedure allows us to calculate the rate of change in prices between $[t - dt, t]$ aggregated for all retailers and all three-digit categories. This means if we set

$dt = 1$, the series $\{\pi_{t,c,s}\}$ represents the daily rate of price change, and by calculating this rate of change for successive periods, we can obtain a price index. Indexes calculated in this manner, that is, by calculating price changes for successive, non-overlapping intervals, are called chained indexes. Because chained indexes measure prices while successively updating information on the sales share of each good at each point in time, they make it possible to swiftly grasp changes in household expenditure patterns.[3] We will discuss more on chaining later.

3.2 Comparison of the POS index with the consumer price index

3.2.1 Construction of the POS monthly index

To compare the daily price index measured using POS data with the CPI published by the Statistics Bureau, we first need to match the data frequency. Because the CPI is a monthly index, we construct a monthly POS index using the following procedure. Using daily POS data, we calculate the sales amount, sales quantity, and unit price for each good i in month T and treat these as monthly data:

$$e_{T,s,i} = \sum_{t \in M_T} e_{t,s,i} \tag{7}$$

$$q_{T,s,i} = \sum_{t \in M_T} q_{t,s,i} \tag{8}$$

$$p_{T,s,i} = \frac{e_{T,c,s}}{q_{T,s,i}} \tag{9}$$

where M_T stands for the set of dates in month T. Using monthly data defined in this way and replacing t with T and dt with dT in equations (1) to (6), we aggregate monthly price changes in the manner described for daily data above.

3.2.2 Correspondence between items in the POS data and the consumer price index

Before we compare the POS index and the CPI, it is necessary to point out a few differences regarding the coverage of the two. While the POS data contain price and quantity information

[3] In contrast, the weights used in the CPI are based on a consumption basket in the base period and are fixed for five years, so that the more time has passed since the base period, the less the rate of change in the price index represents the actual change in prices. In the case of the Laspeyres index, which uses the consumption weights of the base year, if the price of one good rises relative to that of another which is a close substitute, the demand for that good will typically decrease, and vice versa. This means that its consumption weight will fall and the Laspeyres index will overestimate the change in prices, because the weight is based on the consumption pattern of the base year. Similarly, in the case of the Paasche index, which uses the consumption weight in the period for which the index is computed, the effect of a price increase will be underestimated. This means that the Laspeyres index is biased upward, while the Paasche index is biased downward. This type of bias can be reduced by using the chain method instead of fixed weights, and the Statistics Bureau publishes a chained Laspeyres index for reference.

on a wider variety of products than the CPI data within each of the three-digit categories, the expenditure categories covered in the POS data are relatively limited, with food and daily necessities making up the majority of items and fresh food and durable goods (such as electrical appliances), energy, services, etc., not included. In contrast, the CPI is based on data collected for only selected representative goods and services chosen from each category, but covers the whole range of expenditure items, i.e., including fresh food, durable goods, services, etc. Specifically, it focuses on 588 items, for which the price of only one good or, at most, a number of goods (brands) is collected. Thus, whereas the CPI covers a wider range of broad goods and services categories, the POS data cover a much larger number of brands within the categories covered. Of the 588 items surveyed for the CPI, the POS data include 170 items, which, on the basis of the consumption weights (for Japan as a whole) for 2010 based on the FIES make up about 17 percent of total consumption. A list of these 170 items is provided in Table A3.

In order to compare the price index calculated from POS data and the CPI, it is necessary to make the coverage as similar as possible. Therefore, before comparing the two, we construct a CPI based only on those three-digit categories that are included in the POS data, which we call the "CPI (Groceries)." Thus, we aggregate only the 170 CPI items corresponding to categories available in the POS data and calculate the monthly year-on-year inflation rate, which we denote by π_T^O:

$$P_T = \sum_{n=1}^{170} \frac{1_{\{n:P_{T,n}\neq\emptyset\}} W_{T,n}^O}{\sum_{n=1}^{178} 1_{\{n:P_{T,n}\neq\emptyset\}} W_{T,n}^O} P_{T,n} \tag{10}$$

$$\pi_T^O = \frac{P_T - P_{T-dT}}{P_{T-dT}} \tag{11}$$

where $W_{n,T}^0$ is the consumption weight of item n for which a corresponding item in the POS data is available. Given that the sample period for the POS data stretches from 1988 to 2013, there are a number of items that started to be covered in the CPI survey only sometime during this period, so that item-level price indexes are not necessarily available for all items for the entire sample period. Therefore, when calculating P_T, we aggregate price $P_{T,n}$ only for items for which data for each month are available.

Figure 1 compares the π_T^O calculated in this manner, i.e., the CPI (Groceries), and the CPI (All items). We find that although π_T^O is constructed from 170 items, i.e., less than a third of the 588 items in the CPI, the trends of the two are nevertheless very similar. The correlation coefficient of the change on a year earlier in these two monthly indexes is as high as 0.77. The sample period includes two inflationary periods, 1991 and 2008, and both indexes signal an increase in prices around almost the same time. Moreover, for the period from 1995 to 2007 and again from the Lehman shock at the end of 2008 onward both indexes show a negative rate of change, i.e., deflation. However, looking more carefully, there are also

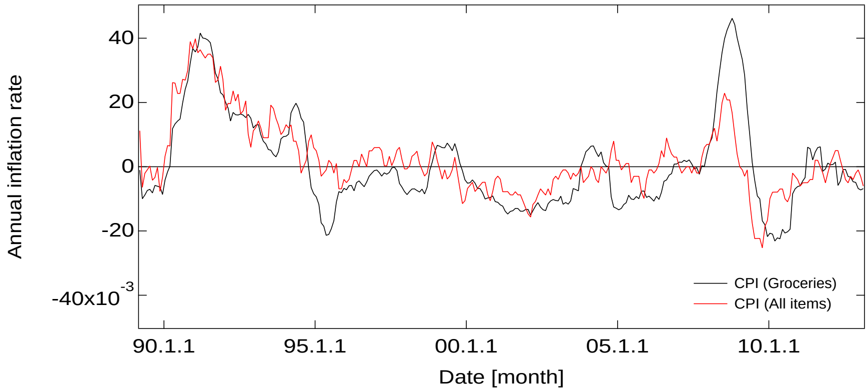

Figure 1: Comparison of the CPI (all items) and the CPI inflation rate for items corresponding to those in the POS data, π_T^O.

occasions on which the two indexes diverge. For example, during the period of inflation in 2008, the rate of inflation based on π_T^O was more than 4 percent, while the rate based on the CPI (All items) was only about 2 percent. The reason for this discrepancy likely is that inflation during this period was caused by the sudden jump in grain prices, which mainly affected food prices, which, in turn, make up a much larger share in the CPI (Groceries) than in the CPI (All items).

4 Results

4.1 Daily and monthly indexes

To what extent is the POS based inflation rate similar to, or different from, the CPI based inflation rate? Let us begin by comparing the daily and monthly POS-based indexes.Panel (a) in Figure 2 shows the rate of inflation measured based on daily prices (black line) and on monthly prices (red line). The daily rate shows the rate of change between a particular day and 365 days before ($dt = 365$), while the monthly rate shows the rate of change between a particular month and the same month in the preceding year ($dT = 12$). The black and red lines show almost identical movements, indicating that monthly prices constructed by pooling daily prices have the same time series properties as the underlying daily prices. However, comparing the changes in daily and monthly prices, the former are much more volatile. Specifically, the standard deviation for the monthly inflation rate is 0.38 percent, while that for the daily inflation rate is 1.09 percent. The daily data contain various seasonal fluctuations such as the day-of-the-week effect, as well as fluctuations stemming from switching between regular and sale prices, and these likely increase volatility. How the volatility of daily inflation

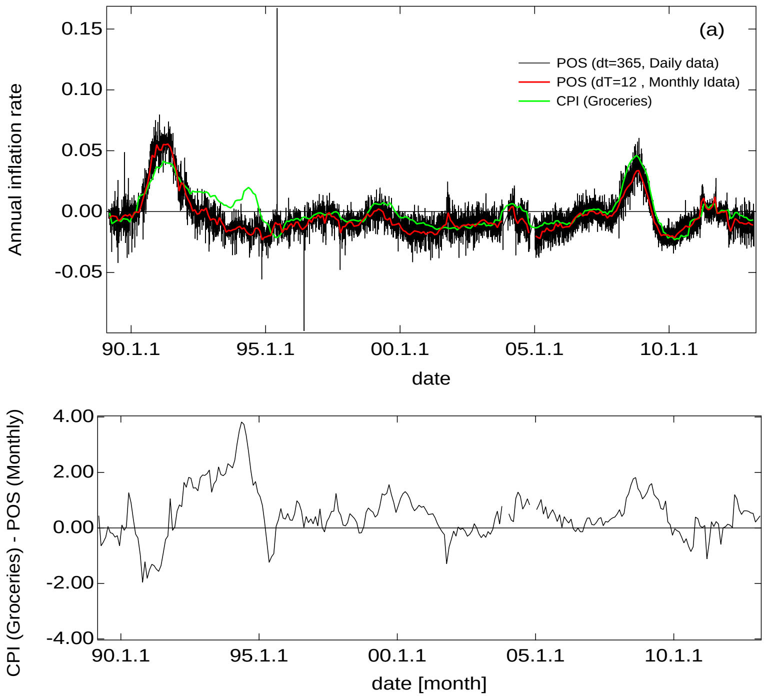

Figure 2: Comparison of the POS-based and CPI-based inflation rates. The black line in panel (a) shows the inflation rate between a particular day and the same day a year earlier measured using daily POS data ($dt = 365$). The inflation rate is defined as $\exp(\pi_t) - 1$. The red line in panel (a) shows the inflation rate between a particular month and the same month in the previous year measured using POS data ($dT = 12$). The inflation rate is defined as $\exp(\pi_T) - 1$. The green line in panel (a) shows the inflation rate between this month and the same month in the previous year based on CPI data for items corresponding to those in the POS data ($\pi_T^O,\ dT = 12$). The line in panel (b) shows the difference between the POS-based monthly inflation rate (the red line in panel (a)) and the CPI-based monthly inflation rate (the green line in panel (a)).

can be reduced will be discussed in greater detail in Section 5.1.

Next, comparing the monthly inflation rate based on the POS data (red line) and the CPI inflation rate for items corresponding to those in the POS data (green line, π_T^O), we find that developments in the two are very similar and the correlation coefficient is 0.83. Both show inflation in 1991 and 2008 and deflationary tendencies during other periods. Panel (b) of Figure 2 shows the difference between the two. This difference is positive in many periods, showing that inflation based on the POS data tends to be lower than that based on the CPI. The average of the difference is 0.48 percentage points, but it varies over time. In other words, there does not exist a simple relationship such that it is only a matter of adding a certain value to the POS inflation rate for it to become the same as the CPI inflation rate. See Handbury, Watanabe and Weinstein (2013) for more on the implications of this fact.

The largest difference between the two inflation measures can be found in the period from 1992 to 1994. Following the collapse of the asset price bubble in the early 1990s, the POS inflation rate drops rapidly and turns negative in June 1992, while the CPI inflation rate remains positive until the summer of 1994 and turns negative only in October 1994. Thus, depending on which of the two measures is used, the point at which the economy fell into deflation differs by 28 months. Moreover, the difference between the two measures also increased during the period of inflation in 2008. Reflecting the increase in energy and grain prices, the CPI-based inflation rate rose to more than 4 percent, while the POS-based inflation rate reached only 3 percent. As shown by Imai and Watanabe (2014), effective price increases during this period occurred in the form of a reduction in the size or weight of products sold, while nominal prices remained unchanged. While part of this effective price increase is reflected in the CPI, it is not reflected in the POS-based inflation rate.

4.2 Item-level inflation

Figure 3 shows fluctuations in the daily POS inflation rates measured for the three-digit categories. The vertical axis represents the category IDs for the three-digit categories (there are 214 three-digit categories), a list of which is presented in Table A2. Category IDs from 1 to 156 are for food and beverages, while category IDs from 157 to 214 are for daily necessities such as shampoos, detergents, and cosmetics. The horizontal axis of the figure shows the date. The inflation rate for a particular category ID on a particular day is represented by the color shown for the corresponding cell. For example, fluctuations in the inflation rate for butter, the category ID of which is 20, can be traced by looking at the 20th row. In the figure, we show the contribution of each category to the overall inflation rate, which is defined by $\omega_{t,c}\pi_{t,c}$, where $\pi_{t,c}$ is the item-level inflation rate given by equation (3), and $\omega_{t,c}$ is the Törnqvist weight given by equation (6).

We see that many cells are red in 1991 and 2008, when the overall inflation rate was relatively high, indicating the emergence of inflation in a wide variety of products.[4] However, looking at the 1991 inflation episode more closely, we find that most of the categories with category IDs from 1 to 150, which represent food and beverages, were red, while few of the categories with category IDs from 151 to 214, which represent daily necessities, were, suggesting that inflation in 1991 was driven largely by food price hikes. Similarly, during the

[4]This is in sharp contrast to the inflation episodes in the 1970s, when prices increased significantly for a particular set of products (i.e., oil-related products) but not that much for other products, and consequently the relative price between oil-related products and other products changed substantially. See Ball and Mankiw (1995) for more on the inflation episodes in the 1970s and the relationship between relative price changes and inflation.

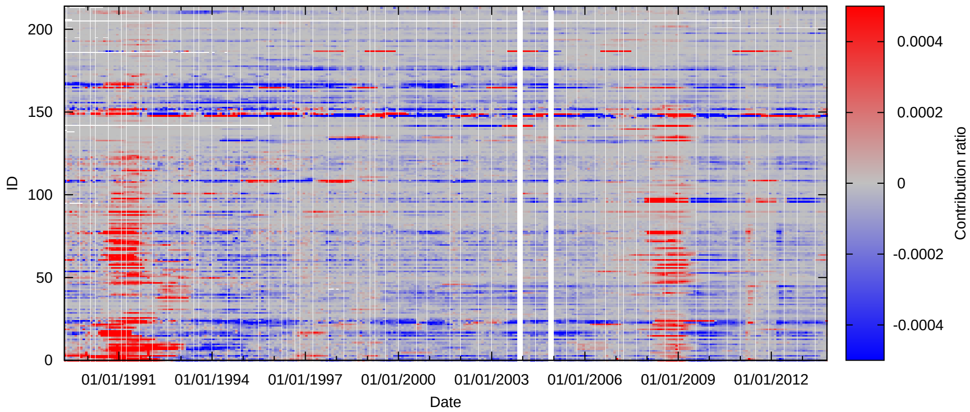

Figure 3: Inflation by item

2008 inflation episode, not all prices rose simultaneously and even among food items (i.e., items with category IDs below 150) there was non-trivial heterogeneity in the rate of inflation, as indicated by the fact that some of the rows changed to red, while others did not. Second, we see that in 1991 some categories turned red a little earlier than other categories. These include category IDs 18 (Ham, bacon), 79 (Packaged instant noodles), and 151 (Fresh eggs). Similarly, in 2008, categories such as 63 (Cooking oil) and 144 (Low-malt beer) turned red earlier than other categories. This suggests the presence of non-trivial heterogeneity across products in terms of the sensitivity to changes in the economic environment and the degree of price stickiness. Third, there are a limited number of categories during the deflationary periods (i.e., 1993-2007 and 2009-2012) that were consistently in dark blue, which indicates a large contribution to deflation. These include the category IDs 25 (Yogurt), 154 (Frozen staple foods), and 169 (Laundry detergent). On the other hand, the other categories are basically either in light blue or in gray during the deflationary periods, indicating that their inflation rates were close to zero even during the deflationary periods. In other words, deflation during these periods was not driven by synchronized price falls across a wide variety of products but was largely due to price declines in products belonging to a limited number of categories.

5 Some additional experiments

5.1 Core inflation

When comparing the daily index ($dt = 365$) and the monthly index ($dT = 12$), we saw that the former fluctuates much more than the latter. Specifically, while the mean of the daily inflation rate is -0.37 percent, the corresponding standard deviation is as high as 1.09 percent. One reason for this large volatility is that a temporary price cut means that there is also a price increase when the price returns to the regular level. While percentage changes in price indexes typically are measured in small single digit numbers, the percentage price change during a temporary sale sometimes can reach several tens of percent. Therefore, such price changes alone give rise to substantial price index volatility.

In addition, however, price changes as a result of temporary sales will also give rise to changes in sales quantities. Specifically, a price drop for a particular good through a temporary sale will lead to rise in the quantity sold. In the Törnqvist approach, this means that a larger weight will be attached to the large price changes through the temporary sale.

Furthermore, individual retailers do not decide independently whether to hold a temporary sale. Looking at the price setting behavior of individual supermarkets in practice, we find that each supermarket or supermarket chain has its own particular practices, such as having temporary sales on a specific day of the week or on specific dates, which are closely correlated with the practices adopted by other supermarkets in the vicinity. Similarly, whether individual goods go on sale is not determined independently; for example, particular goods tend to go on sale simultaneously at a particular time. Because of this correlation of temporary sales across retailers and goods, idiosyncratic factors (i.e., factors underlying price changes by individual retailers or for individual goods) do not necessarily cancel each other out even when prices for a large number of goods are aggregated. In other words, the law of large numbers does not work with regard to the number of retailers or the number of goods, and consequently volatility seen for individual retailers or goods remains.

In this subsection, we make several attempts to reduce the volatility of daily inflation. Specifically, in Section 5.1.1 we try to extract the trend component of daily inflation by employing time series decomposition techniques, while in Section 5.1.2, we examine the usefulness of trimmed mean estimators of inflation by trimming the upper and lower tails of the daily inflation distribution. Trimmed mean estimation is a technique widely employed by central banks to estimate core inflation, although it is usually applied to monthly item-level inflation data to eliminate items with a high volatility at a monthly frequency. In contrast, in this subsection we apply this technique to daily product-level inflation data to help us identify products with a high volatility at a daily frequency and drop them in calculating the aggregate inflation rate.

5.1.1 Time series decomposition

Hodrick and Prescott (1997) assume that time series data consist of a trend component and a cyclical component, and propose a technique to extract the trend component. Specifically, they define the π_t^{HP} that minimizes the following equation as the trend component:

$$\min_{\pi^{HP}} \left\{ \sum_{t=1}^{s} (\pi_t - \pi_t^{HP})^2 + \lambda \sum_{t=2}^{s-1} (\pi_{t+1}^{HP} - 2\pi_t^{HP} + \pi_{t-1}^{HP})^2 \right\} \tag{12}$$

where λ is the smoothing parameter for π_t^{HP}. As shown in the equation above, estimating the trend component π_t^{HP} requires minimizing the sum of the residual sum of squares from the original series and the sum of the squares from the second differences of π_t^{HP} itself. λ is a penalty parameter for large changes in π_t^{HP} over time. If $\lambda = 0$, the original series itself becomes the trend component, whereas if $\lambda \to \infty$, the trend component approaches a straight line. While parameter λ is set by the user, given a frequency of f observations per year, it is usually set to $\lambda = (f/4)^{\beta} * 1600$, while previous studies propose different values for β, with Correia, Neves and Rebelo (1992) suggesting a value of 1, Backus and Kehoe (1992) a value of 2, and Ravn and Uhlig (2002) a value of 4.

Other frequently used trend extraction techniques define trend components by explicitly taking into account that time series data consist of various overlapping cyclical waves and extract waves in a particular frequency range. These include the Baxter-King (BK) filter proposed by Baxter and King (1999) and the Christiano-Fitzgerald (CF) filter proposed by Christiano and Fitzgerald (2003). Both are band pass filters that, by setting a particular bandwidth, attenuate signals outside that bandwidth and extract waves within a frequency range. Applied to our setting here, they are defined as the following weighted moving average:

$$\pi_t^{BP} = \sum_{s=-\infty}^{\infty} B_s \pi_{t+s} \tag{13}$$

where weight B_s is defined by

$$B_s = \begin{cases} \frac{p_l - p_u}{\pi} & (s = 0) \\ \frac{\sin(s\frac{2\pi}{p_l}) - \sin(s\frac{2\pi}{p_u})}{\pi s} & (s \geq 1) \end{cases} \tag{14}$$

with $2 \leq p_l < p_u < \infty$.

Figure 4 compares the trend component extracted using three different types of filters. As can be seen from the figure, no matter which filter is used, the large volatility in the original data is removed and more or less the same trend component is extracted. Next, Figure 5 shows the movement in the trend component around the time of the Tohoku earthquake, which occurred on March 11, 2011. In addition to the three filters, the figure also shows the one-week backward moving average. For the period before the vertical line, which represents March

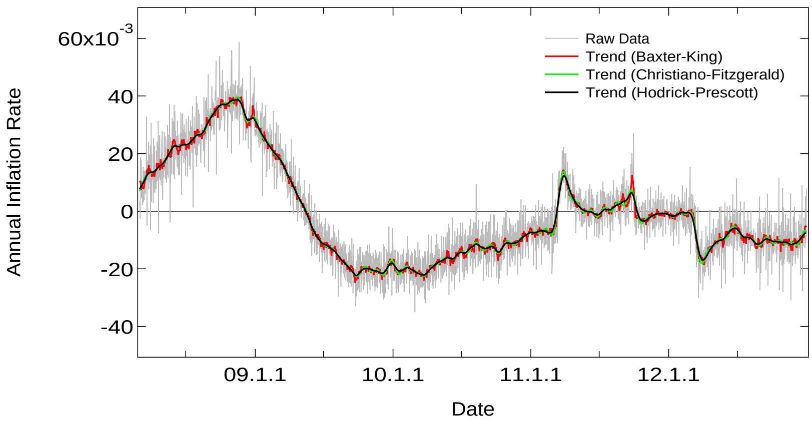

Figure 4: Estimated trend components. The figure shows the trend component estimates obtained by applying the HP filter (black line, $\lambda = 1600$), the BK filter (red line, $f_l = 2, f_u = 32$), and the CP filter (green line, $f_l = 2, f_u = 32$) to the original daily inflation data (grey line).

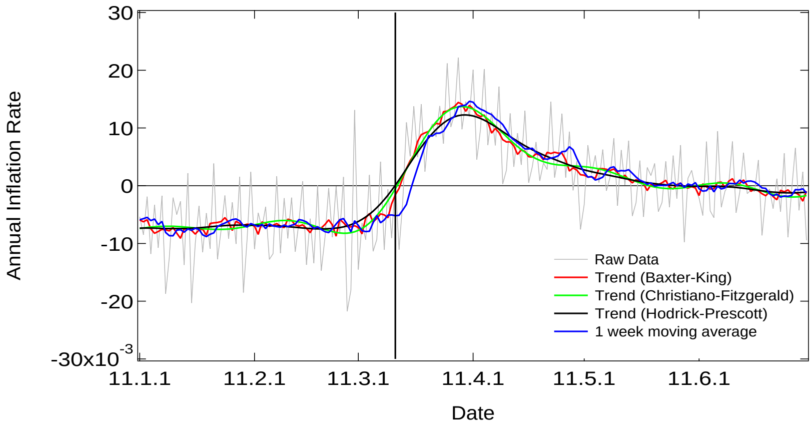

Figure 5: Price movements before and after the Tohoku earthquake (March 11, 2011)

11, all four time series show an annualized deflation rate of around 0.7 percent. However, in the wake of the earthquake the demand for daily necessities such as water and food jumped, resulting in a steep rise in prices and an annualized inflation rate of around 1.5 percent. While this change can also be seen in the original data, it comes out even more clearly by extracting the trend component. However, looking at the results in detail, we find that the trend component extracted using the HP filter shows an increase from about 10 days before the earthquake, because the HP filter uses future observations. Similarly, using the CF filter, the trend component starts to rise about 10 days before the earthquake. The same problem, although to a much smaller extent, can also be seen for the BK filter. Finally, while the one-week backward moving average does not suffer from the problem that it increases before the earthquake, it only shows a gradual price increase after the earthquake, highlighting the flaw of the backward moving average.

5.1.2 Trimmed mean estimators

To the extent that the inflation rate in a given period is caused by large price changes for particular goods and services, it may be desirable to have additional measures of inflation that adjust for those large relative price changes. In particular, these alternative measures would be useful if large relative price changes are a source of temporary fluctuations in the inflation rate. This is the basic idea behind the concept of core inflation, which came into use in the 1970s, when large price increases for energy lead to high overall CPI inflation. For example, since the early 1980s, Japan's Statistics Bureau has been publishing the CPI for all items excluding fresh food as the "core index" and the CPI for all items excluding food and energy as the "core core index."

The concept of core inflation was formalized by Bryan and Cecchetti (1994) and Bryan, Cecchetti and Wiggins (1997).[5] They propose to trim the upper and lower tails of a price change distribution before taking the mean in order to eliminate noise in the inflation measure, reduce inflation volatility, and increase statistical efficiency.[6] In what follows, we apply the trimmed mean method to our daily inflation data. Our exercise differs from previous studies in that we apply the method to daily data, while previous studies apply it to monthly or quarterly data. Another difference is that while previous studies apply the method to the distribution of item-level price changes, we apply it to the distribution of product-level price changes as well as to the distribution of item-level price changes. The reason for applying the method also to the distribution of product-level price changes is that the trimming at the product level will be more effective in reducing inflation volatility, given that inflation volatility at the daily frequency stems largely from the switching between regular and special sales prices.

Let us start with the trimming at the item level. We trim the upper and lower tails of the item-level inflation distribution by α ($0 \leq \alpha \leq 0.5$). To calculate the α-trimmed mean, we first order the sample, $\{\pi_1, \ldots, \pi_c, \ldots, \pi_C\}$, where π_c is the inflation rate for category c given by equation (3), and the associated weights, $\{\omega_1, \ldots, \omega_c, \ldots, \omega_C\}$, which are given by

[5] See Bryan and Cecchetti (1999) and Mio and Higo (1999) for applications of the trimmed mean method to Japanese CPI data.

[6] Rothenberg, Fisher and Tilanus (1964) show that, for the case of Cauchy distributions, discarding observations located in the upper and lower tails of a distribution before taking the mean lowers the sample variance and thereby reduces the efficiency loss.

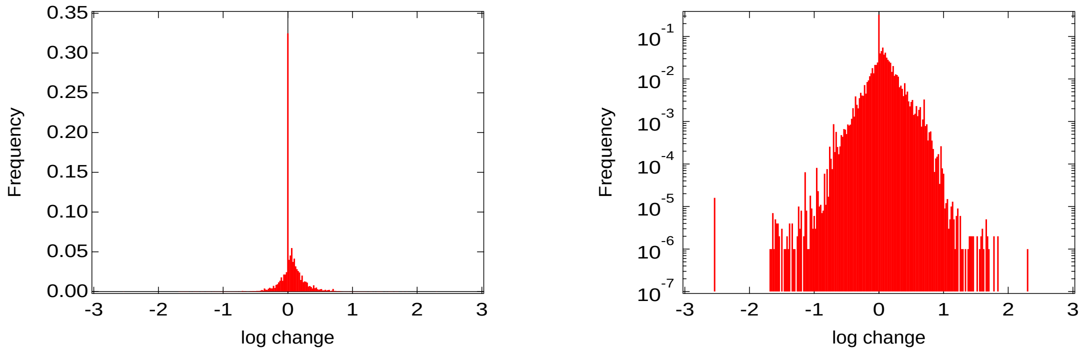

Figure 6: Price change distribution at the product level on a specific day. This distribution is for October 31, 2008. The horizontal axis represents price changes and the vertical axis represents the corresponding weighted densities, where the weight of each observation is defined as the product of $\omega_{t,s,i}$, $\omega_{t,s,c}$, and $\omega_{t,c}$. The vertical axis is in logarithmic scale in the right panel, but not in the left panel.

equation (6). Next, we define F_c as the cumulative weight from 1 to c; that is, $F_c \equiv \sum_{j=1}^{c} \omega_j$. From this we can determine the set of observations to be averaged for the calculation; this is, the c*'s* such that $\alpha < F_c < (1-\alpha)$. We refer to this as I_α. Then the α-trimmed mean can be computed as

$$\frac{1}{1-2\alpha} \sum_{c \in I_\alpha} \omega_c \pi_c \tag{15}$$

There are two obvious special cases: if $\alpha = 0$, this equation gives us the (weighted) mean; if $\alpha = 0.5$, this gives us the (weighted) median. The procedure for trimming at the product level can be defined in a similar manner. That is, we order the sample, which consists of products rather than items, and the associated weights and then trim the upper and lower tails of the distribution by α. However, we identify the set of observations to be trimmed in two different ways. The first is a straightforward extension of the item-level trimming; that is, the trimming operation is applied to the price change distribution for all products. The second way is based on the price change distribution for products belonging to a particular category and sold at a particular retailer. The number of distributions we have is given by the number of categories times the number of retailers. We identify the set of observations to be trimmed for each of the distributions. We refer to the first way of trimming as "global trimming" and the second way as "local trimming." Note that in the local trimming observations are trimmed evenly across categories and retailers, while this is not necessarily the case in global trimming.

Figure 6 shows the distribution of daily price changes at the product level on a specific day. The horizontal axis represents log price changes, while the vertical axis shows the corresponding weighted densities (i.e., observations are not counted with an equal weight, but are counted with a weight given by $\omega_{t,s,i} \times \omega_{t,s,c} \times \omega_{t,c}$). The vertical axis is in logarithmic scale in the right panel but not in the left panel. The figure shows that the price change distribution is extremely fat-tailed, which is consistent with the finding obtained by Bryan and Cecchetti (1999) for the price change distribution in Japan using monthly item-level CPI inflation data. As shown by Bryan, Cecchetti and Wiggins (1997), the sample mean is not the most efficient estimator of the population mean if the data are drawn from a fat-tailed distribution. This is because, in the case of a fat-tailed distribution, one is more likely to obtain a draw from one of the tails of the distribution that is not balanced by an equally extreme observation in the opposite tail. As a result, the sample variance is larger, and thus the sample mean is no longer an efficient estimator. In this case, one may be able to improve efficiency by trimming the upper and lower tails of the sample. Figure 6 suggests that the trimming may work well with our daily data.

Another important feature we see in Figure 6 is that the density corresponding to $\pi = 0$ is extremely high. In other words, there are a large number of products with no price change relative to the price level on the same day in the preceding year.[7] Bryan and Cecchetti (1999) show that, for item-level monthly CPI inflation in Japan, a large proportion of price changes are concentrated in the middle of the distribution. Our finding is similar to theirs but nevertheless differs in that we have an extremely high density only at $\pi = 0$, so that the sample exhibits a discontinuous distribution. An important implication of this fact is that the sample distribution is an asymmetric one. That is, as seen in the figure, observations with non-zero price changes are concentrated at a point slightly above $\pi = 0$, so that the distribution is not symmetric. This is a typical day with a positive inflation rate overall. On the other hand, on a typical day when the inflation rate overall is negative (i.e., we have deflation), observations with non-zero price changes are concentrated at a point slightly below zero, again generating an asymmetric distribution. These results suggest that the population distribution is far from a symmetric distribution. The presence of such asymmetry in price change distributions may influence the usefulness of trimmed mean estimators.

Figure 7 compares the performance of the three trimmed mean estimators in terms of the root mean squared error (RMSE) of each of the three estimators, which is defined as:

$$RMSE \equiv \sqrt{\frac{1}{t_1 - t_0 + 1} \sum_{t=t_0}^{t_1} (TM_t - IT_t)^2} \tag{16}$$

where TM_t is the trimmed mean estimator for period t, IT_t is the inflation trend, and t_0 and t_1 are the start and the end of the sample period. We choose the four-week centered moving

[7]It is well known from recent studies on sticky prices using micro price data that prices are adjusted only infrequently, and as a result, a large portion of products experience no price change in a relatively short period such as day, week, or month.

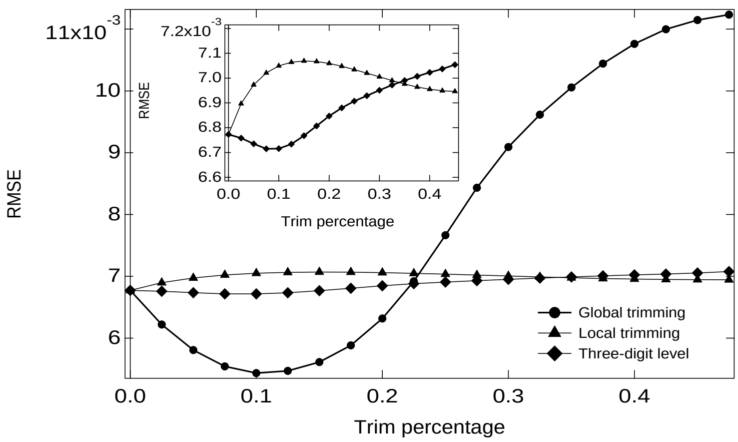

Figure 7: Efficiency of trimmed estimators. The horizontal axis shows the trim percentage, α, while the vertical axis represents the root mean squared error of the corresponding trimmed mean estimator. We choose the four-week centered moving average of π_t as the inflation trend. "Three-digit level" shows the result obtained when applying the trimming to the distribution of item-level inflation rates, while "Global trimming" and "Local trimming" show the results obtained when applying the trimming to the distributions of product-level inflation rates. In the global trimming, the trimming operation is applied to the distribution of all product-level inflation rates, while in the local trimming the trimming operation is applied to the distribution of product-level inflation rates for products belonging to a particular category and sold at a particular retailer.

average of π_t as the measure of the inflation trend.[8] The vertical axis of Figure 7 shows the RMSE measured in this way, while the horizontal axis represents the trim percentage, α. The sample period is 2000 to 2013. The line labeled "Three-digit level" shows the result obtained when we trim the price change distribution at the item level. We see that the RMSE changes slightly depending on the trim percentage. The small chart, which presents a selective magnification of the main chart, shows that the RMSE is minimized at $\alpha = 0.1$, indicating that the trimmed mean estimator with $\alpha = 0.1$ is the most efficient in the sense that it comes closest to the inflation trend. Bryan and Cecchetti (1999) and Mio and Higo (1999) conduct a similar exercise using item-level monthly CPI data for Japan and find that the RMSE is minimized when the trim percentage is 15 percent (Mio and Higo (1999)) or 30 percent (Bryan and Cecchetti (1999)). Our result is comparable to theirs despite the difference in data frequency. However, the efficiency gain is much smaller in our case. For example, according to Mio and Higo (1999), the RMSE is 6 percent smaller at $\alpha = 0.15$ than

[8]To check the robustness of the result, we tried four different window lengths: 1 week, 2 weeks, 4 weeks, and 12 weeks. The result remained unchanged.

at $\alpha = 0$. The corresponding figure in our case is only 1.5 percent.

Turning to the trimming at the product level, the line for "Global trimming" in the main chart of Figure 7 shows that the RMSE is minimized at $\alpha = 0.1$ and that the efficiency gain is 21 percent (i.e., the RMSE at $\alpha = 0.1$ is 25 percent smaller than that at $\alpha = 0$), indicating that the product-level trimming works much better than the item-level trimming. This result implies that large price changes are not necessarily concentrated in a particular product category but can take place in any category. Finally, the line for "Local trimming" shows that the RMSE does not decline much with α, clearly rejecting that large price changes are equally likely to occur in each category or at each retailer.

5.2 Decomposing daily inflation into regular and sale price changes

Recent studies on price stickiness using micro price data, including those by Eichenbaum, Jaimovich and Rebelo (2011) and Nakamura and Steinsson (2008), show that regular prices are much stickier and less volatile than actual prices. These results suggest that one may be able to reduce volatility by calculating daily inflation based on regular prices. Moreover, if one decomposes daily inflation fluctuations into those due to changes in regular prices and those due to switching between regular and sale prices, one can learn more about the underlying causes of daily inflation fluctuations, especially about retailers' pricing behavior. For example, given that adjustments of regular prices tend to be infrequent and irreversible, if a rise in daily inflation is due to a rise in regular prices, this can be interpreted as signaling that retailers will likely continue to raise prices in the future. In this case, one may predict that the price increases will be highly persistent. In contrast, if a rise in daily inflation stems either from less frequent temporary sales or from smaller sales discount rates, this means that retailers' policy of raising the price average may not be that persistent, so that the rise in inflation may not last that long.

To examine this, we therefore decompose π_t from Section 3 into two components: the component related to regular price changes and the component related to the switching between regular and sale prices. We begin by denoting π_t as $\pi_t = \sum_s \sum_i \hat{\omega}_{i,s,t} \Delta \ln p_{i,s,t}$, where $\Delta \ln p_{i,s,t} \equiv \ln \frac{p_{i,s,t}}{p_{i,s,t-dt}}$ and $\hat{\omega}_{i,s,t} \equiv \omega_{i,s,t}\omega_{s,c,t}\omega_{c,t}$. Given this definition, we decompose

π_t as follows:

$$\pi_t = \underbrace{\sum_s \sum_i 1_{\{\Delta \ln p^R_{i,s,t} \neq 0\}} \hat{\omega}_{i,s,t}}_{\text{Frequency of regular price changes}} \underbrace{\frac{\sum_s \sum_i 1_{\{\Delta \ln p^R_{i,s,t} \neq 0\}} \hat{\omega}_{i,s,t} \Delta \ln p^R_{i,s,t}}{\sum_s \sum_i 1_{\{\Delta \ln p^R_{i,s,t} \neq 0\}} \hat{\omega}_{i,s,t}}}_{\text{Size of regular price changes}}$$
$$+ \underbrace{\sum_s \sum_i 1_{\{\Delta \ln p_{i,s,t} \neq \Delta \ln p^R_{i,s,t}\}} \hat{\omega}_{i,s,t}}_{\text{Frequency of sales}} \underbrace{\frac{\sum_s \sum_i 1_{\{\Delta \ln p_{i,s,t} \neq \Delta \ln p^R_{i,s,t}\}} \hat{\omega}_{i,s,t} (\Delta \ln p_{i,s,t} - \Delta \ln p^R_{i,s,t})}{\sum_s \sum_i 1_{\{\Delta \ln p_{i,s,t} \neq \Delta \ln p^R_{i,s,t}\}} \hat{\omega}_{i,s,t}}}_{\text{Size of sales}} \tag{17}$$

where $p^R_{i,s,t}$ represents the regular price for good i sold at retailer s in period t. We will explain how we measure $p^R_{i,s,t}$ in a moment, but given that $p^R_{i,s,t}$ is observable, it is straightforward to decompose daily inflation π_t into the component related to regular price changes, which is represented by the first term on the right-hand side of the above equation, and the component related to the switching between regular and sale prices, which is represented by the second term of the equation. Note that the term labeled "frequency of sales" reflects not only a sale event in period t but also a sale event in period $t-dt$. For example, if retailer s sells good i at a regular price in period $t-dt$ but sells it at a sale price in period t, then $\Delta \ln p_{i,s,t} \neq \Delta \ln p^R_{i,s,t}$. Similarly, if retailer s sells good i at a sale price in period $t-dt$ but sells it at a regular price in period t, again $\Delta \ln p_{i,s,t} \neq \Delta \ln p^R_{i,s,t}$. Also, if retailer s sells good i at a sale price in period $t-dt$ and again sells it at a sale price in period t, but the two sale prices are different, then $\Delta \ln p_{i,s,t} \neq \Delta \ln p^R_{i,s,t}$.[9]

Next, we compute regular prices. Using the Nikkei data, Sudo, Ueda and Watanabe (2014) calculate the regular price of a good i sold by retailer s in period t as the most commonly observed price, i.e., the mode price, during the 6 weeks before and after period t. We employ the same method here. In other words, $p^R_{i,s,t}$ is computed as the 12-week centered moving mode of the original price level, $p_{i,s,t}$. This method has been used in various previous studies, including Eichenbaum, Jaimovich and Rebelo (2011) and Abe and Tonogi (2010), although the window length used by Abe and Tonogi (2010) to calculate the mode price is shorter than ours.[10]

[9] Also, note that if $\Delta \ln p_{i,s,t} - \Delta \ln p^R_{i,s,t} = 0$ and $\Delta \ln p_{i,s,t} \neq 0$, the change in $p_{i,s,t}$ is regarded as reflecting a change in the regular price. On the other hand, if $\Delta \ln p_{i,s,t} - \Delta \ln p^R_{i,s,t} \neq 0$ and $\Delta \ln p_{i,s,t} = 0$, it means that a switching between regular and sale prices occurs between t and $t - dt$ although no price change is observed in terms of $p_{i,s,t}$.

[10] Various papers propose alternative methods to discriminate regular and sale prices, including Nakamura and Steinsson (2008), who propose to use a sale filter to detect a sale event making use of the fact that prices go back to their original level after a sale event. Note that the mode price is referred to as the reference price by Eichenbaum, Jaimovich and Rebelo (2011) and others, which may not necessarily be identical with the regular price. However, in this paper, we do not distinguish between the two.

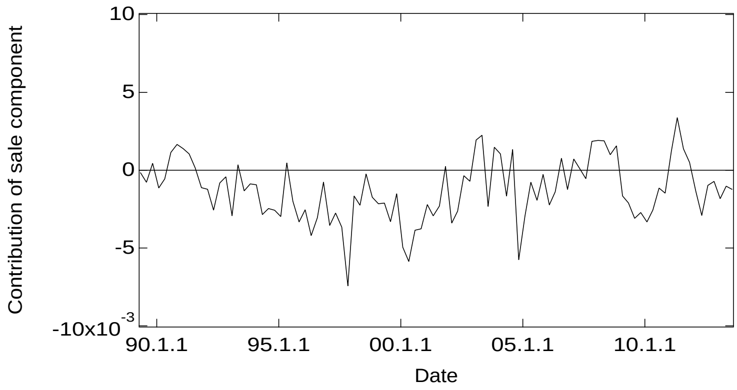

Figure 8: The contribution of sales to fluctuations in the daily inflation rate. The contribution of sales is computed based on a daily frequency and converted to a quarterly frequency.

Figure 8 shows the extent to which the sale component, which is represented by the second term on the right-hand side of equation (17), contributed to fluctuations in the daily inflation rate. The sale component takes a positive value in 1991 and 2008, when the overall inflation rate was positive, implying that during these inflationary periods, retailers lowered the frequency of temporary sales or reduced the size of sale discounts relative to the same day in the previous year. Less frequent sales and smaller sale discounts contributed to raising π_t by around 0.5 percentage points. However, the sale component lowered π_t in other years, meaning that retailers increased the frequency of temporary sales or raised the sale discount. This tendency is particularly clear in 1995-2002 and 2010, when the overall inflation rate was negative (i.e., there was deflation), and the contribution of the sale component to π_t reached more than 5 percentage points. Given that the rate of deflation in these years was at most 2 percent, we can say that temporary sales made a substantial contribution to the emergence of deflation during this period.

Next, Figure 9 compares fluctuations in the daily inflation rate based on actual prices (red line) and based on regular prices (black line) since January 2011. The black line represents the first term on the right-hand side of (17), while the vertical distance between the red and black lines corresponds to the sale component. As we saw earlier, the daily inflation rate based on actual prices exhibited a sharp rise at the time of the Tohoku earthquake (March 11, 2011) from -0.7 percent to +1.5 percent. One may be interested in how much of that change is accounted for by regular price changes and how much by the sale component. During this period, the inflation rate based on regular prices increased from -0.7 percent to +0.2 percent, indicating that regular price changes made some contribution to raising π_t. However, the distance between the red and black lines widened substantially during this period, implying

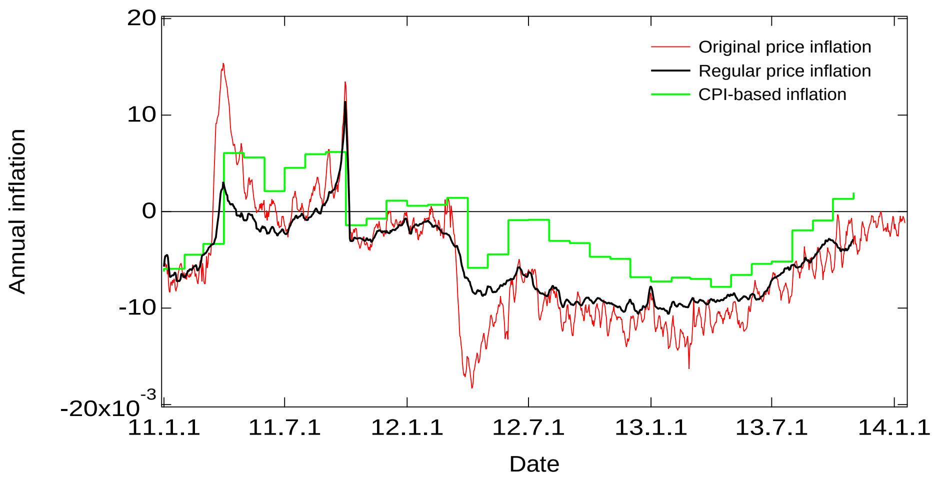

Figure 9: The inflation rate based on regular prices. The actual and the regular price inflation rates are shown by the red and the black line respectively. The regular price in period t for product i sold at retailer s, denoted by $p^R_{i,s,t}$, is computed as the 12-week centered moving mode of the actual price level, $p_{i,s,t}$, which was defined in Section 3.1. The regular price inflation rate is calculated by aggregating $\ln p^R_{i,s,t}/p^R_{i,s,t-dt}$ over i and s using the corresponding weights. The green line is the CPI-based monthly inflation rate.

that the sale component played a much more important role in raising π_t. This suggests that retailers reacted to the substantial increase in demand in the wake of the earthquake by reducing the frequency of temporary sales or lowering the sale discount, which may be seen as a rational response, given that the increase in demand could be seen as temporary.

A notable upward trend in the inflation rate can also be observed in the most recent period since December 2012, when Prime Minister Shinzo Abe launched a set of economic policies that has come to be referred to as "Abenomics," with the daily inflation rate going up from -1.4 percent in late 2012 to almost zero percent in January 2014. Is this increase in π_t due to changes in regular prices or due to changes in temporary sales? Interestingly, the increase in π_t is mostly due to regular price changes, while the contribution of the sale component is of limited importance. This may be interpreted as suggesting that retailers' perception regarding the persistence of the demand increase driven by aggressive monetary policy easing is quite different from the demand increase at the time of the earthquake.

5.3 Chained Törnqvist index

The daily inflation rate shown in the previous section is calculated by setting $dt = 365$, i.e., by comparing the price of a product on a particular day and the price of the product on the same day in the previous year. The set of products used in this calculation consists of those

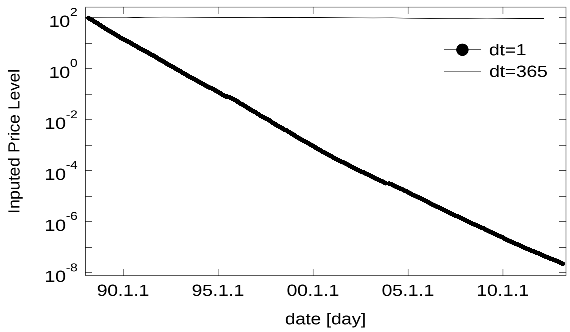

Figure 10: Chained Törnqvist indexes. The value for the base period (March 1, 1988) is set to 100 for each case (i.e., $100 \times \exp\left(\sum_{s=0} \pi_s\right)$).

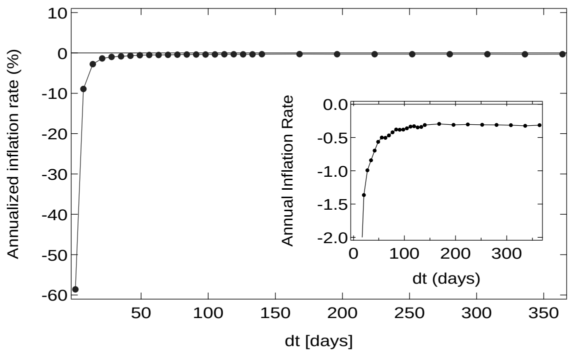

Figure 11: The relationship between the time interval and the measured inflation rate

products available on both that particular day and the same day a year earlier. Products that disappeared sometime between that day and the same day a year earlier are not included in the calculation. Similarly, products that were newly born somewhere between the two days are also not included. However, as widely mentioned in previous studies, product turnover is very high in scanner data. For example, the entry and exit rates in our dataset (i.e., the number of new or disappearing products in a year relative to the total number of products at the start of the year) were 36 percent and 35 percent, respectively. Given this high product turnover, it would not be ideal to drop new and disappearing products from the calculation. One way to obtain more product matches is to choose a shorter interval between the two days compared, i.e., to set a smaller dt. Obviously, the largest number of matches would be obtained by setting $dt = 1$, where the prices of products on a particular day and the day immediately before are compared. In this case, most of the products available on that day are used for the calculation, except for the few products that were newly introduced on that day. Thus, to take advantage of the fact that product turnover from one day to the next is much smaller than that over longer periods of time, one can calculate the inflation rate from $t-1$ to t, that from t to $t+1$, that from $t+1$ to $t+2$, and so on, and then link them. This is referred to as a chained index. Chained superlative indexes, such as chained Törnqvist and chained Fisher indexes, are of particular importance.

However, chained superlative indexes measured using scanner data have a well known drawback. As pointed out by Szulc (1983) and Feenstra and Shapiro (2003) among others, high frequency chaining leads to drift in weighted indexes when prices and weights oscillate or "bounce." To illustrate this, Figure 10 compares the Törnqvist index for $dt = 1$ and $dt = 365$, with the value for the base period (March 1, 1988) in each case set to 100. The figure shows that when $dt = 1$, the chained index has a substantial downward trend, which is called a downward chain drift. Over the entire sample period of about 25 years the price index falls to a tiny fraction of the base value of about 10^{-10}, for a decline that is equivalent to an annual deflation rate of 60 percent.

To investigate this issue in more detail, we calculate the inflation rate for different values of dt. Figure 11 shows the result of this exercise, with he horizontal axis representing the time interval dt and the vertical axis the corresponding annualized inflation rate. For $dt = 1$, the annualized rate of inflation is -60 percent, which is what we saw in Figure 10. However, the measured inflation rate shrinks rapidly with dt and ultimately converges to a certain number. Using a different scale for the vertical axis, the small chart in Figure 11 allows a more detailed examination. The chart shows that the rate of deflation falls rapidly until $dt = 100$, but once dt becomes greater than 100, the measured inflation rate hardly changes and converges to around -0.3 percent. This result suggests that chain drift is indeed a serious problem at frequencies of less than a quarter year, but for longer frequencies it is small enough to be ignored from a practical perspective. This result can be interpreted as reflecting the fact that the shorter the time interval when measuring the inflation rate, the larger is the effect of sales on individual prices and quantities.

How does high frequency chaining lead to chain drift? To address this, let us consider a simple example. Specifically, let us consider a period of four days, during which goods are sold at the regular price on the first day, but there is a sale on the second and third day; the goods are then sold at the regular price again on the fourth day. Specifically, we assume that

$$\frac{p_{i,s,2}}{p_{i,s,1}} = \frac{p_{i,s,3}}{p_{i,s,4}} \equiv \exp(-\delta); \quad \frac{p_{i,s,3}}{p_{i,s,2}} = 1 \tag{18}$$

where $p_{i,s,t}$ denotes the price of good i sold by retailer s on day t ($t = 1, 2, 3, 4$) as in the previous sections, and δ is the special sale discount rate. We begin by considering the case in which goods are not storable. We assume a translog demand equation in which the consumption share of a product depends linearly on the relative price of the product (i.e., the log difference between the price of the product and the general price level). Given this specification of demand, (18) implies

$$\begin{aligned} s_{i,s,2} - s_{i,s,1} &= -\gamma\left(\ln p_{i,s,2} - \ln p_{i,s,1}\right) = \gamma\delta \\ s_{i,s,3} - s_{i,s,2} &= -\gamma\left(\ln p_{i,s,3} - \ln p_{i,s,2}\right) = 0 \\ s_{i,s,4} - s_{i,s,3} &= -\gamma\left(\ln p_{i,s,4} - \ln p_{i,s,3}\right) = -\gamma\delta \end{aligned} \tag{19}$$

where $s_{i,s,t}$ is the share of the amount of sales of good i at retailer s in the amount of sales of all goods at all retailers (i.e., $s_{i,s,t} \equiv e_{i,s,t}/\sum_s \sum_i e_{i,s,t}$) and γ is a positive parameter associated with the relative price term in the translog demand equation. Note that in this simple example, we assume that the general price level in the translong demand equation does not change over time. Given (19), we can compute the corresponding Törnqvist weights as

$$\tilde{\omega}_{i,s,2} = s_{i,s,1} + \gamma\delta/2; \quad \tilde{\omega}_{i,s,3} = s_{i,s,1} + \gamma\delta; \quad \tilde{\omega}_{i,s,4} = s_{i,s,1} + \gamma\delta/2 \tag{20}$$

where $\tilde{\omega}_{i,s,t}$ is a Törnqvist weight when $dt = 1$ and is defined as $\tilde{\omega}_{i,s,t} \equiv (s_{i,s,t} + s_{i,s,t-1})/2$. Finally, given equations (18) and (20), we can calculate the rate of inflation between $t = 1$ and $t = 4$ based on the chained Törnqvist index as

$$\tilde{\omega}_{i,s,2} \ln \frac{p_{i,s,2}}{p_{i,s,1}} + \tilde{\omega}_{i,s,3} \ln \frac{p_{i,s,3}}{p_{i,s,2}} + \tilde{\omega}_{i,s,4} \ln \frac{p_{i,s,4}}{p_{i,s,3}} = 0 \tag{21}$$

On the other hand, a direct comparison between prices at $t = 1$ and $t = 4$ indicates that $\frac{s_{i,s,1}+s_{i,s,4}}{2} \ln \frac{p_{i,s,4}}{p_{i,s,1}} = 0$, which is identical to the result obtained by chaining, indicating that there is no chain drift in the case of non-storable goods.

However, this no longer holds if goods are storable. In this case, consumers have an incentive to stack up on the goods on the days of the sale ($t = 2, 3$). On the one hand, this increases their purchases during the sale; on the other, it reduces their purchases before the sale ($t = 1$) and/or immediately after the sale ($t = 4$). In the case that consumers reduce their purchases before the sale, $s_{i,s,2} - s_{i,s,1}$ is no longer equal to $\gamma\delta$ but is greater than $\gamma\delta$, so that

$$\tilde{\omega}_{i,s,2} \ln \frac{p_{i,s,2}}{p_{i,s,1}} + \tilde{\omega}_{i,s,3} \ln \frac{p_{i,s,3}}{p_{i,s,2}} + \tilde{\omega}_{i,s,4} \ln \frac{p_{i,s,4}}{p_{i,s,3}} > 0$$

indicating that the inflation rate based on the chained Törnqvist index now has an upward drift. On the other hand, if consumers reduce their purchases immediately after the sale, $s_{i,s,4} - s_{i,s,3}$ is smaller than $-\gamma\delta$, so that

$$\tilde{\omega}_{i,s,2} \ln \frac{p_{i,s,2}}{p_{i,s,1}} + \tilde{\omega}_{i,s,3} \ln \frac{p_{i,s,3}}{p_{i,s,2}} + \tilde{\omega}_{i,s,4} \ln \frac{p_{i,s,4}}{p_{i,s,3}} < 0$$

again indicating the presence of chain drift, but this time it is a downward drift.

In recent studies using scanner data from Australia and the Netherlands respectively to examine chain drift in superlative indexes, Ivancic, Diewert and Fox (2011) and de Haan and Van der Grient (2011) find evidence of a downward drift. Ivancic, Diewert and Fox (2011) argue that the downward chain drift they observe in the data likely stems from the fact that when a product comes off sale, consumers are likely to purchase less than the average quantity of that product for a while until their inventories of the product have been depleted, which is the situation described in the latter case of our simple example. Meanwhile, de Haan and Van der Grient (2011) in the data for the Netherlands find some empirical evidence that fewer purchases by consumers immediately after a sale are onesource of downward chain drift. On the other hand, Feenstra and Shapiro (2003), using US scanner data on canned tuna, found that the weekly chained Törnqvist index has an upward bias, because quantities sold were not high during the initial period of a sale and that retailers tended to advertise sales during the final period of the sale, so that quantities sold tended to be higher towards the end of the sales. Our example above did not address the case where the sales quantities differ on the days of the sale, but it is straightforward to show that an upward drift arises when the quantities sold in $t = 4$ are greater than in $t = 3$.[11]

To examine the potential sources of the downward chain drift observed in our scanner data, we decompose the daily inflation rate based on the chained Törnqvist index as follows:

$$
\begin{aligned}
\tilde{\pi}_t \;=\; & \frac{1}{2} \underbrace{\frac{\sum_{(i,s)\in R_t} e_{i,s,t}}{\sum_s \sum_i e_{i,s,t}}}_{\text{Expenditure share}} \underbrace{\sum_{(i,s)\in R_t} \frac{e_{i,s,t}}{\sum_{(i,s)\in R_t} e_{i,s,t}} \ln \frac{p^R_{i,s,t}}{p^R_{i,s,t-1}}}_{\text{Size of reg price change}} \\
+ \; & \frac{1}{2} \underbrace{\frac{n^D_t}{n_t}}_{f^D_t} \underbrace{\frac{\sum_{(i,s)\in D_t} e_{i,s,t}/n^D_t}{\sum_s \sum_i e_{i,s,t}/n_t}}_{x^D_t} \underbrace{\sum_{(i,s)\in D_t} \frac{e_{i,s,t}}{\sum_{(i,s)\in D_t} e_{i,s,t}} \left(\ln \frac{p_{i,s,t}}{p_{i,s,t-1}} - \ln \frac{p^R_{i,s,t}}{p^R_{i,s,t-1}} \right)}_{u^D_t} \\
+ \; & \frac{1}{2} \underbrace{\frac{n^D_t}{n_t}}_{f^D_t} \underbrace{\frac{\sum_{(i,s)\in D_t} e_{i,s,t-1}/n^D_t}{\sum_s \sum_i e_{i,s,t-1}/n_t}}_{y^D_t} \underbrace{\sum_{(i,s)\in D_t} \frac{e_{i,s,t-1}}{\sum_{(i,s)\in D_t} e_{i,s,t-1}} \left(\ln \frac{p_{i,s,t}}{p_{i,s,t-1}} - \ln \frac{p^R_{i,s,t}}{p^R_{i,s,t-1}} \right)}_{v^D_t} \\
+ \; & \frac{1}{2} \underbrace{\frac{n^U_t}{n_t}}_{f^U_t} \underbrace{\frac{\sum_{(i,s)\in U_t} e_{i,s,t}/n^U_t}{\sum_s \sum_i e_{i,s,t}/n_t}}_{x^U_t} \underbrace{\sum_{(i,s)\in U_t} \frac{e_{i,s,t}}{\sum_{(i,s)\in U_t} e_{i,s,t}} \ln \left(\ln \frac{p_{i,s,t}}{p_{i,s,t-1}} - \ln \frac{p^R_{i,s,t}}{p^R_{i,s,t-1}} \right)}_{u^U_t} \\
+ \; & \frac{1}{2} \underbrace{\frac{n^U_t}{n_t}}_{f^U_t} \underbrace{\frac{\sum_{(i,s)\in U_t} e_{i,s,t-1}/n^U_t}{\sum_s \sum_i e_{i,s,t-1}/n_t}}_{y^U_t} \underbrace{\sum_{(i,s)\in U_t} \frac{e_{i,s,t-1}}{\sum_{(i,s)\in U_t} e_{i,s,t-1}} \left(\ln \frac{p_{i,s,t}}{p_{i,s,t-1}} - \ln \frac{p^R_{i,s,t}}{p^R_{i,s,t-1}} \right)}_{v^U_t} \qquad (22)
\end{aligned}
$$

where $\tilde{\pi}_t$ is the Törnqvist inflation rate from yesterday to today, so that one can calculate the chained inflation rate for a certain period by adding up the $\tilde{\pi}_t$ over that period (i.e., $\sum_t \tilde{\pi}_t$). R_t is the set of products whose regular price changes between day $t-1$ and day t. D_t is the set of products whose price declines from $t-1$ to t due to the start of a sale on day t, and n^D_t is the number of those products. Similarly, U_t is the set of products whose price increases from $t-1$ to t due to the end of a sale on day $t-1$ (i.e., day $t-1$ is the final day of the sale), and n^U_t is the number of those products. Finally, n_t is the number of products available on day t.

Since we would like to investigate the changes in $\tilde{\pi}_t$ due to sales, let us focus on the second

[11] See Szulc (1983), Hill (1993), and Reinsdorf (1999) for more on the potential sources of chain drift.

Table 1: Tests to compare two distributions

Null hypothesis	Mean Welch test	Median Wilcoxon test	Distribution Kolmogorov-Smirnov test
$f^D = f^U$	0.577	0.099*	0.016**
$u^D = -v^U$	0.713	0.698	0.313
$u^U = -v^D$	0.469	0.210	0.047**
$x^D = y^U$	0.057*	0.008***	0.016**
$x^U = y^D$	0.290	0.248	0.170

Note: Each figure in the table represents the p-value associated with the respective null hypotheses. ***, **, and * indicate that the null hypothesis is rejected at a significance level of 1, 5, and 10 percent, respectively. The sample period for each variable is August 12, 2002 to August 11, 2003, with the number of observations 365.

to fifth terms on the right-hand side of equation (22), which, using a set of new notations, can be rewritten as

$$\frac{1}{2} f_t^D \left(x_t^D u_t^D + y_t^D v_t^D \right) + \frac{1}{2} f_t^U \left(x_t^U u_t^U + y_t^U v_t^U \right) \tag{23}$$

where f_t^D is the fraction of products which go on a sale on day t, while f_t^U is the fraction of products for which the sale ends on the day before t. The two fractions are not necessarily the same every day, but they must equal each other over the sample period; that is, we should expect $\sum_t f_t^D = \sum_t f_t^U$. Moreover, u_t^D measures the size of the price declines on day t due to the start of sales, which is computed using a Paasche weight, while v_t^U measures the size of the price increases on day t due to the end of sales, which is also computed using a Paasche weight. Again, the two – that is, the size of the price declines and the size of the price increases – do not necessarily have to be the same every day, but they must equal each other over the sample period, so that $\sum_t u_t^D = -\sum_t v_t^U$ holds. Similarly, $\sum_t u_t^U = -\sum_t v_t^D$ must hold.

Turning to the other variables in (23), x_t^D is the expenditure share on the day when the sale starts, while y_t^U is the expenditure share on the final day of a sale period. As we saw in the illustrative example above, the translog demand equation implies that, as long as goods are not storable, the expenditure shares must be identical once they are aggregated over time (that is, $\sum_t x_t^D = \sum_t y_t^U$). Finally, y_t^D is the expenditure share one day before the sale starts and x_t^U is the expenditure share one day after the sale ends. Therefore, $\sum_t x_t^U = \sum_t y_t^D$ must hold if goods are not storable. In sum, as long as goods are not storable, the following must hold:

$$\begin{aligned}
&\sum_t f_t^D = \sum_t f_t^U; \\
&\sum_t u_t^D = -\sum_t v_t^U; \quad \sum_t u_t^U = -\sum_t v_t^D; \\
&\sum_t x_t^D = \sum_t y_t^U; \quad \sum_t x_t^U = \sum_t y_t^D.
\end{aligned} \tag{24}$$

We conduct tests to see whether these equations hold in the data. Specifically, we compute a time series of each variable and then look at the sample distribution of each variable in terms of its mean and median. In this process, several issues that need careful treatment arise. First, as for the sample period, we need to make sure that $\sum_t \tilde{\pi}_t$ is sufficiently close to zero, because we do not want the results to be distorted by the presence of positive or negative trend inflation. We chose the one-year period from August 12, 2002 to August 11, 2003 as the sample period for this calculation. Second, since, as mentioned earlier, the rate of product turnover is high, it is likely that a sale for a good starts on a particular day, but that good disppears before the sale period ends. If this is the case, the start of a sale is recorded in the data, but the end of the sale is not recorded. Obviously, equation (24) does not hold in this case. To avoid this, we choose a set of products that are available throughout the sample period and focus only on those products. Finally, as mentioned in previous studies such as Ivancic, Diewert and Fox (2011), there is a tendency for products not to sell well when they come off a sale. Such a decline in the quantity sold is not a problem in the context of our analysis, as long as the quantity is not exactly zero. If it does fall to zero, there is no sales record in our scanner data for the product for that day, so that we cannot calculate the price of the product on that day. One way to deal with this issue is to impute prices. For example, we could use the price on the day immediately before the missing observation. Alternatively, we could focus only on products for which sales records are available throughout the sample period. We tried both methods and obtained essentially similar results. In what follows, we present the result based on the second method.

The result is shown in Table 1, where the column labeled "Mean" presents the p-value associated with the null hypothesis that two distributions are identical in terms of their mean. For example, the p-value associated with the null hypothesis that the distribution u^D and the distribution $-v^U$ have an identical mean is 0.692, clearly not rejecting the null. We have similar results for the other pairs except for the pair x^D and y^U, for which the p-value is 0.057, rejecting the null hypothesis at the 10 percent significance level. In the next column, we repeat the same exercise using the median, again finding that the null is rejected only for the pair x^D and y^U. In the last column, we use the Kolmogorov-Smirnov test to compare two distributions, which again shows that the distributions are not identical for the pair x^D

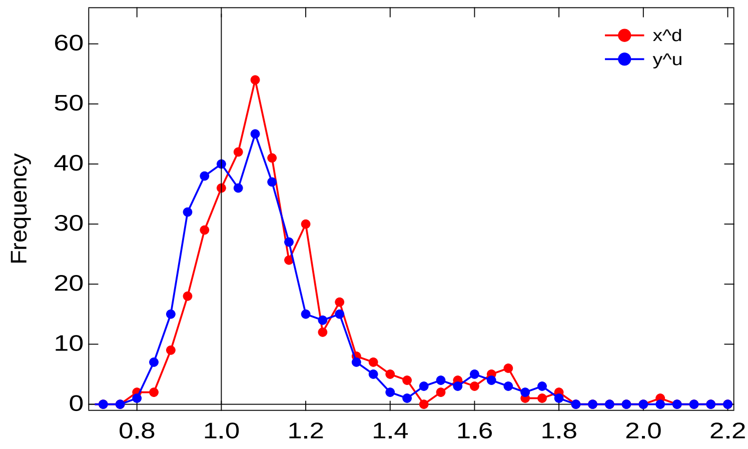

Figure 12: The distributions of the expenditure shares on the first and the final day of a sale period. The red line shows the distribution of the expenditure share on the first day of a sale period, x^D, while the blue line shows the distribution of the expenditure share on the final day of a sale period, y^U. The sample period is August 12, 2002 to August 11, 2003, with the number of observations 365.

and y^U, although the null is also rejected for the pair f^D and f^U and the pair u^U and $-v^D$. Figure 12 compares the distribution of x^D and that of y^U, clearly showing that x^D tends to be greater than y^U.

As x^D and y^U represent the expenditure shares on the first and the final day of a sale period, the result above means that goods sell more on the first day than on the final day. If we go back to equation (22), we can see that this will produce a downward chain drift. This finding is similar to Feenstra and Shapiro's (2003) observation that quantities sold differed during a sale period and that this is a source of chain drift. However, in their case, quantities sold tended to increase toward the end of a sale period, so that they find an upward chain drift in the data. In contrast, we find that quantities sold are higher on the first day of a sale period than on the final day, resulting in a downward drift. It should also be emphasized that our result differs from Ivancic, Diewert and Fox's (2011) observation that quantities sold are smaller immediately after a sale ends and that it is this that gives rise to a downward drift. Our result shows that quantities sold are indeed smaller immediately after a sale period ends, but it also shows that quantities sold are smaller before a sale period starts. Importantly, according to equation (22), what is key is not whether quantities sold are smaller after a sale period ends, but whether quantities sold are equally small before and after a sale period. Our result shows that quantities sold are equally small before and after a sale period, so that the sale does not produce any substantial drift.

6 Conclusion

In this paper, we constructed a Törnqvist daily price index using POS data spanning the quarter-century from 1988 to 2013. We found that developments in the year-on-year rate of inflation measured using this index closely resembled those measured using data for the corresponding items in the CPI. Specifically, the correlation between the two was 0.83. However, the two indexes differ in a number of important respects.

First, the inflation rate based on the POS data tends to fall below that based on the CPI. The difference between the two during the sample period on average is 0.48 percentage points. However, the difference between the two varies over time. The difference is greatest from 1992 to 1994, when, following the collapse of the asset price bubble in 1991, the POS inflation rate drops rapidly and turns negative in June 1992, while the CPI inflation rate remains positive until summer 1994 and turns negative only from October 1994. Thus, depending on which of the two indexes is used, the point at which the economy fell into deflation differs by 28 months. In this context, it is interesting to note that a widespread criticism of the Bank of Japan is that it started to loosen monetary policy too late during this period, and the results obtained here suggest that one of the reasons for this is that the CPI reflected the slide into deflation too late. The difference between the two indicators also increased during the period of inflation in 2008. Reflecting the increase in grain and energy prices, the CPI-based inflation rate rose to more than 4 percent, while the POS-based inflation rate reached only 3 percent. During this period, effective price increases occurred in the form of a reduction in the size or weight of products sold, while prices per package, etc., remained unchanged. While part of this effective price increase is reflected in the CPI, it is not reflected in the POS-based inflation rate, and part of the difference in the measured inflation rates for 2008 likely is due to this reason.

Second, the standard deviation for the daily change in the POS data is 1.09 percent compared to a standard deviation for the monthly change in the CPI of 0.29 percent, indicating that the daily POS data is much more volatile. This likely reflects frequent switching between regular and sale prices. We employed various approaches to reduce the high volatility in daily inflation, including the use of trimmed mean estimators. While these are widely used by central banks to extract inflation trends from the monthly CPI, we found that they are also useful in reducing daily inflation volatility. We showed that trimmed mean estimators are particularly useful when applied to a price change distribution at the product level rather than at the item level, and that the volatility in daily inflation can be reduced by more than 10 percent.

Finally, if we measure price changes from one day to the next and construct a price index by linking these changes, a strong drift arises so that the price index falls to 10^{-10} of the base value over the 25-year sample period, which is equivalent to an annual deflation rate of 60 percent. We provide some evidence suggesting that a source of the chain drift is fluctuations in sales quantities before, during, and after temporary sales.

In sum, using scanner data for the construction of superlative price indexes potentially provides a useful way forward to gain a better understanding of price developments and to help in a more timely detection of changes in inflation trends. This would be of considerable interest not only from an academic perspective, but could also help in the construction of price indexes by statistical agencies and the appropriate conduct of monetary policy. However, there are a number of issues we have to solve before that. As our discussion of core inflation has shown, high frequency inflation measures contain a lot of noise, which makes it harder to identify inflation trends. Thus, while high frequency inflation data are potentially useful in detecting the impact of a variety of events (such as policy announcements by the central bank or changes in the exchange rate) on retailers' pricing behavior, actually doing so will be difficult without reducing noise. As we showed in this paper, trimmed mean estimators provide a potentially useful tool in this regard, but a lot of noise still remains to be removed. Moreover, as our discussion on chain drift has shown, a much deeper understanding of the sources of chain drift is required, which would provide the basis for the development of methodologies to remove such drift. Finally, the limited range of goods for which scanner data are available is also a serious issue. Taking these things into consideration, employing scanner data is not a straightforward matter. This paper represents an attempt to consider some of the potential benefits and pitfalls encountered using scanner data. However, much remains to be done.

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Table A1: Overview of the Nikkei POS data

Year	No. of retailers	No. of products	Sales amount (yen)	No. of records
1988	29	88,207	24,967,387,530	25,397,753
1989	45	118,459	38,848,140,951	39,967,625
1990	50	131,217	47,914,018,985	46,449,145
1991	53	133,201	56,554,113,519	50,762,796
1992	62	135,862	67,325,003,923	56,069,411
1993	65	139,929	75,403,002,651	61,371,512
1994	103	157,148	115,779,158,308	91,670,103
1995	124	169,366	149,242,076,718	119,894,820
1996	132	177,116	180,557,355,210	150,298,311
1997	150	194,522	205,874,958,531	171,939,036
1998	172	218,661	262,631,787,495	218,298,976
1999	172	225,503	265,603,874,575	226,063,598
2000	189	250,497	276,182,400,451	242,140,503
2001	187	264,994	301,163,033,600	274,076,220
2002	198	275,815	313,697,755,019	283,176,100
2003[1]	189	259,242	264,127,818,448	242,227,335
2004	202	278,894	306,121,269,565	281,899,515
2005	187	287,680	328,939,470,128	309,625,996
2006	189	305,223	334,615,509,093	323,381,091
2007	274	347,185	373,166,817,586	378,924,802
2008	261	367,064	407,677,569,675	412,836,053
2009	264	357,928	404,988,058,786	416,290,153
2010	259	358,282	395,223,198,995	415,348,828
2011	249	358,813	380,908,900,263	403,645,269
2012	261	356,587	399,628,611,703	445,046,118

[1] Because original data for November and December are missing, the figures show the totals for January to October.

Table A2: Three-digit categories in the Nikkei POS data

Tofu, soy products	Curry	Alcohol-related beverages
Natto (fermented soybeans)	Stew, hashed beef	Maternity, baby food
Konjac (amorphophallus konjac)	Instant soup	Nutrition supplement foods
Pickled vegetables	Instant miso soup, Japanese style soup	Gift certificates, gift sets
Simmered soy beans and sweetened mash	Pasta sauce	Cereal grains
Tsukudani (small seafood)	Packaged instant noodles	Fresh eggs
Delicatessen, lunch boxes	Instant cup noodles	Special dietary requirement food
Kamaboko (fish cake)	Instant foods	Frozen staple foods
Chikuwa (tube-like food product made from fish)	Ochazuke, furikake seasoning	Frozen meals
Boiled fish paste products	Instant seasoning for rice dishes	Ice cream
Fried fish paste products	Instant seasoning for cooking	Premium ice cream
Processed seafood	Sausages stuffed with fish paste products	Ice
Egg products	Instant soup cups	Shampoo
Chilled semi-finished products	Packaged instant raw noodles	Soap
Chilled condiments	Instant cup raw noodles	Bath salts
Fresh noodles, boiled noodles	Canned agricultural product	Toothpaste
Ham, bacon	Canned fruit	Toothbrushes
Sausages	Canned desserts	Mouth freshener
Meat products	Canned seafood	Portable sanitary sets
Butter	Canned meat	Sanitary feminine products
Margarine, fat spread	Canned side dishes	Birth control supplies
Natural cheese	Bottled agriculture product	Paper products for daily use
Processed cheese	Bottled seafood	Disposable diapers
Yogurt	Bottled meat	Laundry detergent
Milk	Bread loafs	Kitchen detergent
Milk beverages	Bread (croissant, baguette, muffin, etc.)	Household cleaner
Lactic acid bacteria beverages	Steamed bread and pastry	Deodorant, odor neutralizer, disinfectant
Fresh cream	Prepared bread meals	De-humidifier
Soy milk	Cereals	Insecticides, rodenticides
Chilled dessert	Rice cakes	Mothballs
Chilled cake	Jam	Care, hygiene products
Coffee beverages	Spreads	Denture care products
Cocoa and chocolate beverages	Honey, syrup	Basic skin care for women
Tea beverages	Dessert mixes	Cosmetics for women
Green tea beverages	Flour mixes	Women's hair care products
Barley tea beverages	Cake and bread ingredients	Fragrances
Oolong tea beverages	Regular coffee	Cosmetics for men
Herbal tea beverages	Instant coffee	Cosmetic accessories
Carbonated beverages	Cocoa, milk for drink mixes	Men's hair care products
Fruit juice beverages	Tea	Etiquette products
100% fruit juice beverages	Green tea	Razors
Vegetable juice	Barley tea	Home medical supplies
Sports drinks, isotonic drinks	Oolong tea, herbal tea	Baby food products
Diluted beverages	Non-fat powdered milk, powdered cream	Tobacco, smoking accessories
Nutrition support drinks	Chocolate	Toilet and bath products
Water	Chewing gum	Washing and drying equipment
Seaweed	Candy, candy confections	Home cleaning products
Dried marine products	Snack foods	Miscellaneous goods
Flour, dry mixtures	Baked western confectionery	Toilet cleaning supplies
Sesame seeds	Dessert cake	Cooking, kitchen supplies
Dried beans	Rice crackers	Kitchen sink accessories
Dried vegetable products	Japanese-style confectionery	Food containers
Dried noodles	Japanese traditional treats	Mops
Dried pasta	Confectionery with toys	Disposable tableware
Sugar, sweeteners	Bean snacks	Leisure food products
Salt	Marine delicacies	Sink accessories
Miso paste (soybean paste)	Meat delicacies	Batteries
Koji (rice malt)	Nuts	Electronic storage media
Soy sauce	Dried fruit	Stationery and paper products
Vinegar, vinegar-related seasonings	Assortments of sweets	Daily use stationery
Mirin, cooking sake	Japanese sake	Writing utensils
Cooking oil	Beer	Painting supplies
Table sauces (okonomiyaki, tonkatsu)	Whiskey, brandy (liquors)	Office automation supplies
Tomato flavored seasonings	Shochu	Office paperwork organization supplies
Mayonnaise	Wine	Hanging hooks
Salad dressing	Liqueur	Pet sanitary products
Umami seasonings (flavor enhancer)	Spirits	Dog food
Instant bouillon	Chinese liquor	Cat food
Spices	Cocktail drinks	Pet food (except for dogs and cats)
Mixed seasonings, spices and condiments	Miscellaneous liquors	Consumable houseware gift sets
Cooking base	Low-malt beer	
Seasoning sauce	Low alcohol drinks	

Table A3: Correspondence between items in the consumer price index and the three-digit categories

CPI item name	Item code	Three-digit category
Domestic rice A	1001	Cereal grains
Domestic rice B	1002	Cereal grains
Glutinous rice	1011	Cereal grains
Bread loafs	1021	Bread loafs
Sweet bean paste bun	1022	Steamed bread and pastry
Curry doughnut	1023	Steamed bread and pastry
Boiled udon (thick wheat noodles)	1031	Fresh noodles, boiled noodles
Dried udon (thick wheat noodles)	1041	Dried noodles
Spaghetti	1042	Fresh noodles, boiled noodles
Instant noodles	1051	Packaged instant noodles, packaged instant raw noodles, instant cup nooldes, instant cup raw noodles
Fresh Chinese noodles	1052	Fresh noodles, boiled noodles
Wheat flour	1071	Wheat flour
Rice cakes	1081	Rice cakes
Fried kamaboko (fish cake)	1151	Fried fish paste products
Chikuwa*	1152	Chikuwa*
Kamaboko (fish cake)	1153	Kamaboko (fish cake)
Dried bonito flakes	1161	Dried marine products
Seafood tsukudani	1166	Tsukudani**
Canned seafood	1173	Canned seafood
Salted fish guts	1163	Processed seafood
Ham	1252	Ham, bacon
Sausages	1261	Sausages
Bacon	1271	Ham, bacon
Milk (retail sales)	1303	Milk
Powdered milk	1311	Non-fat powdered milk, powdered cream
Yogurt	1333	Yogurt
Butter	1321	Butter
Cheese	1331	Natural cheese, processed cheese
Cheese (imported)	1332	Natural cheese, processed cheese
Eggs	1341	Fresh eggs
Adzuki beans	1451	Dried beans
Dried shiitake mushrooms	1453	Dried vegetable products
Seaweed	1461	Seaweed
Wakame (seaweed)	1462	Dried marine products
Kelp	1463	Dried marine products
Hijiki (seaweed)	1464	Dried marine products
Tofu	1471	Tofu, soy products
Deep-fried tofu	1472	Tofu, soy products
Natto (fermented soybeans)	1473	Natto (fermented soybeans)
Konjac (amorphophallus konjac)	1481	Konjac (amorphophallus konjac)
Umeboshi (pickled plum)	1482	Pickled vegetables, delicatessen
Radish pickles	1483	Pickled vegetables, delicatessen
Chinese cabbage pickles	1486	Pickled vegetables, delicatessen
Kimchi (Korean pickles)	1487	Pickled vegetables, delicatessen
Kelp tsukudani	1485	Tsukudani**
Canned fruit	1591	Canned fruit
Cooking oil	1601	Cooking oil
Margarine	1602	Margarine, fat spread
Salt	1611	Salt
Soy sauce	1621	Soy sauce
Miso paste (soybean paste)	1631	Chilled condiments
Sugar	1632	Sugar, sweeteners
Vinegar	1633	Vinegar, vinegar-related products
Sauces	1641	Chilled condiments
Salad dressing	1645	Salad dressing
Ketchup	1642	Tomato flavored seasonings
Mayonnaise	1643	Mayonnaise
Jam	1644	Chilled condiments
Curry sauce mix	1652	Curry
Instant soup	1653	Instant soup

* Chikuwa: Tube-like food product made from ingredients such as fish surimi, salt, sugar, starch, monosodium glutamate and egg white

** Tsukudani: Small seafood, meat or seaweed simmered in soy sauce and mirin

CPI item name	Item code	Three-digit category
Flavor seasoning	1654	Umami seasonings (flavor enhancer), instant bouillon
Furikake seasoning	1656	Ochazuke, furikake seasoning
Liquid seasoning	1655	Chilled condiments
Pasta sauce	1658	Pasta sauce
Sweet bean jelly	1701	Japanese-style confectionery
Manju	1702	Japanese-style confectionery
Daifukumochi (rice cake with sweet filling)	1703	Japanese-style confectionery
Sponge cake	1711	Dessert cake
Cake	1712	Chilled cake
Jelly	1784	Chilled dessert
Pudding	1714	Chilled dessert
Cream puffs	1713	Chilled cake
Rice crackers	1741	Rice crackers
Biscuits	1721	Baked western confectionery
Potato chips	1783	Snack foods
Candy	1732	Candy, candy confections
Chocolate	1761	Chocolate
Ice cream	1782	Regular ice cream, premium ice cream
Peanuts	1772	Nuts
Chewing gum	1781	Chewing gum
Sushi (lunch box)	1795	Delicatessen, lunch boxes
Lunch boxes (other than lunch boxes)	1791	Delicatessen, lunch boxes
Rice balls	1793	Delicatessen, lunch boxes
Prepared bread meals	1792	Prepared bread meals
Frozen prepared pilaf	1794	Frozen meals
Prepared pasta	1796	Instant foods
Grilled eel	1801	Processed seafood
Salad	1811	Delicatessen , lunch boxes
Croquettes	1821	Chilled semi-finished products
Pork cutlets	1831	Frozen meals
Fried chicken	1842	Meat products
Yakitori (grilled chicken)	1843	Meat products
Gyoza (dumplings)	1881	Chilled semi-finished products
Frozen prepared croquettes	1851	Frozen meals
Frozen prepared hamburgers	1852	Frozen meals
Prepared curry	1871	Curry
Seasoning mix for rice	1891	Ochazuke, furikake seasoning
Simmered soy beans	1812	Simmered soy beans and sweetened mash (chestnuts, beans or sweet potatoes)
Grilled fish	1802	Delicatessen, lunch boxes
Kimpira (chopped sauteed vegetables)	1813	Delicatessen, lunch boxes
Green tea	1902	Green tea
Tea	1911	Tea
Tea beverages	1914	Green tea, black tea, oolong tea, herbal tea beverages
Instant coffee	1921	Instant coffee
Coffee beans	1922	Regular coffee
Coffee beverages	1923	Coffee beverages
Fruit juice	1930	Fruit [juice] beverages
Fruit juice beverages	1931	Soft drinks
Vegetable juice	1941	Vegetable juice
Carbonated beverages	1951	Carbonated beverages
Lactic acid bacteria beverages A	1971	Diluted beverages
Lactic acid bacteria beverages B	1972	Lactic acid bacteria beverages
Mineral water	1982	Water
Sports drinks	1981	Sports drinks, isotonic drinks
Sake	2003	Japanese sake
Distilled spirits	2011	Shochu
Beer	2021	Beer
Low-malt beer	2026	Low-malt beer
Whiskey	2033	Whiskey, brandy (liquors)
Wine	2041	Wine
Wine (imported)	2042	Wine
Chuhai (shochu highball)	2012	Cocktail drinks
Beer-like alcoholic beverages	2027	Beer-like beverages
Tissue paper	4412	Paper products for daily use
Toilet paper	4413	Paper products for daily use
Kitchen detergent	4431	Kitchen detergent
Laundry detergent	4441	Laundry detergent
Plastic wrap	4401	Cooking, kitchen supplies
Plastic bags	4402	Cooking, kitchen supplies
Insecticides	4451	Insecticides, rodenticides
Mothballs	4461	Mothballs
Fabric softener	4442	Laundry detergent
Room freshener	4471	Deodorant, odor neutralizer, disinfectant
Kitchen paper	4403	Cooking, kitchen supplies
Disposable diapers (for infants)	6141	Disposable diapers
Disposable diapers (for adults)	6142	Disposable diapers
Ball pen	9111	Writing utensils
Marking pen	9115	Writing utensils
Notebooks	9121	Stationery and paper products
Office paper	9127	Office automation supplies
Cellophane adhesive tape	9124	Daily use stationery
Recordable disc	9198	Electronic storage media
Compact disc	9172	Electronic storage media
Video software	9174	Electronic storage media

CPI item name	Item code	Three-digit category
Pet food (dog food)	9193	Dog food
Pet food (cat food)	9196	Cat food
Batteries	9195	Batteries
Printer ink	9128	Office automation supplies
Electric razors	9602	Razors
Toothbrushes	9611	Toothbrushes
Facial wash	9627	Soap
Toilet soap	9621	Soap
Body soap	9626	Soap
Shampoo	9622	Shampoo
Hair conditioner	9624	Shampoo
Toothpaste	9623	Toothpaste
Hair styling products	9631	Women's hair care products, men 's hair care products
Hair tonic	9641	Women's hair care products, men 's hair care products
Cosmetic cream A	9650	Basic skin care for women
Cosmetic cream B	9652	Basic skin care for women
Skin toner	9661	Basic skin care for women
Skin lotion A	9690	Basic skin care for women
Skin lotion B	9692	Basic skin care for women
Foundation A	9670	Cosmetics for women
Foundation B	9672	Cosmetics for women
Lipstick A	9680	Cosmetics for women
Lipstick B	9682	Cosmetics for women
Hair color	9625	Women's hair care products, men 's hair care products
Cigarettes (domestic)	9799	Cigarettes, smoking accessories
Cigarettes (imported)	9798	Cigarettes, smoking accessories