Online Appendix: On the Source of Seasonality in Price Changes: The Role of Seasonality in Menu Costs

By KO MUNAKATA, SHIGENORI SHIRATSUKA, TAKESHI SHINOHARA, NAO SUDO, AND TSUTOMU WATANABE*

AUGUST 2024

* Munakata: Bank of Japan (e-mail: kou.munakata@boj.or.jp); Shinohara: Bank of Japan (e-mail: takeshi.shinohara@boj.or.jp); Shiratsuka: Keio University (e-mail: shigenori.shiratsuka@keio.jp); Sudo: Bank of Japan (e-mail: nao.sudou@boj.or.jp); Watanabe: University of Tokyo (e-mail: watanabe@e.u-tokyo.ac.jp).

A. Model

We extend the simple partial equilibrium menu cost model for firms by Nakamura and Steinsson (2008) to include seasonally varying parameters. Each month, firms, which are subject to idiosyncratic shocks, decide whether to adjust their price by paying a menu cost. The firm's policy function is influenced by cyclical variations in parameters. These parameter values change during a cycle, which consists of six months, and return to the original values after the cycle. In this setting, the total inflation rate over 1 cycle is exogenously given, whereas the monthly inflation rate as well as the frequency and size of price increases/decreases for each month are endogenously determined by firms' responses to seasonally varying parameters. We refer to this equilibrium as the cyclical steady state equilibrium.

In our model, firm z with idiosyncratic productivity $A_t(z)$ has linear production function

$$y_t(z) = A_t(z)L_t(z),$$

where the logarithm of idiosyncratic productivity follows an AR(1) process

$$\log\left(A_t(z)\right) = \rho\log\left(A_{t-1}(z)\right) + \varepsilon_t(z), \quad \varepsilon_t(z) \sim N(0, \sigma_\varepsilon^2).$$

Firm z faces demand $y_t(z)$ that depends both on its own price level $p_t(z)$ and on the aggregate price level P_t according to

$$y_t(z) = C\left(\frac{p_t(z)}{P_t}\right)^{-\theta}.$$

Firms face a common real marginal cost, given by

$$\omega_{m(t)} = \frac{W_{m(t)}}{P_t}$$

where $m(t)$ denotes the month of time t satisfying $m(t) = \mathrm{mod}(\mathrm{t}-1,6)+1$ and $W_{m(t)}$ is the nominal wage rate. As in the model by Nakamura and Steinsson (2010), in order to adjust their prices, firms have to hire additional workers and pay a menu cost given by

$$W_{m(t)}K_{m(t)}.$$

Firms' real profit can be written in the following form:

$$\Pi_t(z) = \frac{p_t(z)y_t(z) - W_{m(t)}L_t(z)}{P_t} - \frac{W_{m(t)}K_{m(t)}}{P_t}1\left(p_t(z) \neq p_{t-1}(z)\right),$$

which can be rewritten as

$$\Pi_t(z) = C\left(\frac{p_t(z)}{P_t}\right)^{-\theta}\left(\frac{p_t(z)}{P_t} - \frac{\omega_{m(t)}}{A_t(z)}\right) - \omega_{m(t)}K_{m(t)}1\big(p_t(z) \neq p_{t-1}(z)\big).$$

The optimization problem that each firm faces in this model is therefore written as

$$V_{m(t)}\left(\frac{p_{t-1}(z)}{P_t}, A_t(z)\right) = \max_{p_t(z)}\left[\Pi_t(z) + \beta \mathrm{E}_t V_{m(t+1)}\left(\frac{p_t(z)}{P_{t+1}}, A_{t+1}(z)\right)\right].$$

In model A described in the main text, $K_3 > K_1 = \mathrm{K}_2 = \mathrm{K}_4 \cdots = \mathrm{K}_6$, while $\omega_{m(t)}$ is constant. In contrast, in models B and C, $\omega_{m(t)}$ varies with the month, while $K_{m(t)}$ is constant. In each model, under the seasonally varying parameter values, we seek the cyclical steady state satisfying $V_{m(t)} = V_{m(t+6)}$ and $ln(P_{t+6} / P_t) = \pi^* = 0.01$. The values of the other parameters mostly follow those used in Nakamura and Steinsson (2008) and are shown in Figure 13 in the main text.

We use the following iterative algorithm to obtain the solution:

(i) Specify finite grid points for the state variables $p_{t-1}(z) / P_t$ and $A_t(z)$.

(ii) Assume a particular path of monthly inflation rate $\pi_{m(t)} = \ln(P_t / P_{t-1})$.

(iii) Given the monthly inflation rate in (ii), solve the firms' optimization problem described above by value function iteration to obtain monthly policy functions.

(iv) From the monthly policy functions and the idiosyncratic productivity process, calculate the density of firms on the grid for each month.

(v) Using the monthly density and monthly policy function, calculate the endogenous path of the monthly inflation rate.

(vi) Repeat steps (iii) to (v) until convergence.

B. Description of the POS Data

Our data is Point-of-Sale (POS) scanner data collected by Nikkei Digital Media from retail shops located in Japan. The data have been widely used by existing studies on micro-level price dynamics in Japan, including Abe and Tonogi (2010), Sudo et al. (2014), Sudo et al. (2018), and Ueda et al. (2019). The data are daily and the sample period covers the period from March 1, 1988 to February 10, 2022, excluding November and December of 2003. The data are taken from 575 stores and the sampled stores are spread across Japan. According to Abe and Tonogi (2010), among the sampled stores, even small stores have 2,000 customers a day. The data consist of 11 billion records and each record contains the number of units sold and sales in yen for product i, identified by 13-digit Japanese Article Number (JAN) code, at shop s on date d. The cumulative number of products appearing during the sample period is 1.8 million.

The data include processed food and domestic articles and, unlike the CPI, do not include fresh food, recreational durable goods, such as TVs and PCs, and services, such as rent and utilities. The coverage of the POS scanner data in the CPI is 201 out of 582 items, which constitutes 20.5% of households' expenditure covered by the official CPI with the base year of 2020.

For the purpose of the analysis, we aggregate the 13-digit JAN product level data to a 3-digit level, such as “tofu,” “yogurt,” “beer,” “tobacco,” and “laundry detergent,” as defined by Nikkei and hereafter refer to the data aggregated at this level as a “category.” Table B1 shows the list of categories studied in this paper.

We exclude the data of years 1988, 1989, 2003, 2004 and 2022 from our analysis, either because the data of some months are missing (1988, 2003, and 2022), the data needed for computing the regular price of some months are missing (2004), or because of a complication associated with the introduction of the consumption tax (1989). Consequently, the data period for our analysis is reduced to that from the beginning of January 1990 to the end of December 2021, excluding the years 2003 and 2004.

We also make adjustments to the sampled products and categories. First, we exclude products whose first and last days of sale are separated by less than 365+90 days. This is because the “monthly changes in the seasonal pattern” of the “regular price” of such products cannot be well measured due to the constraint associated with our filtering methodologies of regular prices and seasonal components of the prices. Second, for each category, we identify the years that contain months with fewer than 15 regular price increases or decreases per month and exclude these years from the sample to accurately measure the size of price changes. After that, we drop 18 categories that have short sample periods (less than 15 years). Consequently, we use 199 categories out of 217 categories for our analysis.

Figure B1 shows the time path of the aggregate POS inflation rate obtained by the scanner data together with the CPI inflation rate. Note that the latter represents the CPI of goods less fresh food and energy so that the coverage becomes close to that of the scanner data. There are some commonalities in the way that the two series have developed.[1] For example, both series exhibit a high inflation rate during the early 1990s followed by a decline in the inflation rate lasting until the early 2000s. They also both exhibit a sharp decline after the global financial crisis.

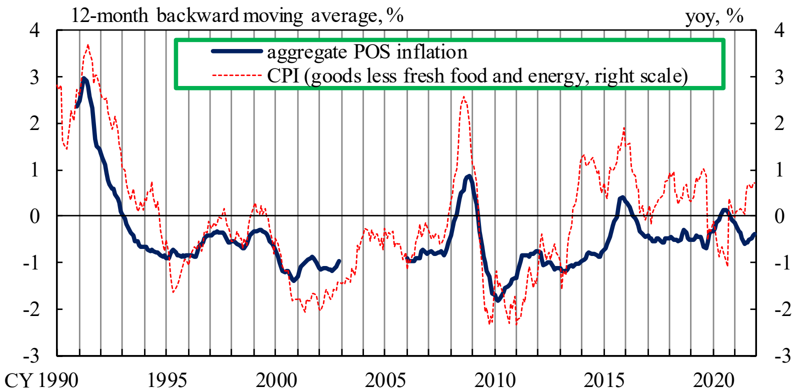

FIGURE B1. AGGREGATE POS INFLATION

Notes: The CPI figures exclude the effects of the consumption tax hikes. Aggregate POS inflation is calculated as the weighted average of the inflation rate for each category weighted by sales.

[1] Clearly, there are differences in terms of how the two series have developed during the sample period. In terms of the compiling methodology, the official CPI and our POS inflation differ mainly in the following three aspects. First, the scope of the sample is different. While our POS inflation uses data on all products sold in the sampled stores to calculate an index for each of the categories, the CPI first selects specific products that are considered representative and then makes calculations based on the prices of those products only. Second, the definition of regular price differs. The regular price in the CPI is defined as the price on any one day from Wednesday through Friday of the week containing the 12th of each month and that lasts for at least eight days. On the other hand, the regular price in our POS inflation calculation is, as discussed in the main text, calculated by taking the mode in a rolling window. Third, when a firm changes the quantity of a product without changing its price, the CPI and our POS data treat this change differently: in the CPI, an increase (decrease) in the quantity of some items at the same price is measured as a price reduction (price increase). In our POS inflation calculation, such cases are measured as the exit of an old product and the entry of a new product since the barcode has changed.

TABLE B1—CATEGORIES IN THE POS DATA

Tofu and tofu products	Nabe-soup	Alcohol-related beverages
Natto (fermented soybeans)	Curry	Baby and maternity food
Konnyaku	Stew and hayashi	Nutritional supplements
Pickles	Instant soups	Food gift sets and gift certificates
Cooked soybeans and kinton	Instant miso soup and Japanese soup	Grains
Tsukudani	Pasta sauce	Fresh eggs
Side dishes and bento	Instant noodles	Nursing and sick food
Kamaboko (fish paste)	Instant cup noodles	Frozen ingredients
Chikuwa	Instant foods	Frozen side dishes
Fish paste products	Furikake and chazuke	Regular ice cream
Deep-fried fish paste products	Rice-related instant seasonings	Premium ice cream
Processed marine products	Instant seasonings for cooking	Ice
Egg products	Fish paste products in casing	Vegetables for heating
Chilled semi-finished products	Instant soups and juices in cups	Mushrooms
Chilled seasonings	Raw instant noodles	Hair wash
Fresh and boiled noodles	Raw instant cup noodles	Soap
Ham and bacon	Canned agricultural products	Bath salts
Sausage	Canned fruits	Toothpaste
Meat Products	Canned desserts	Toothbrushes
Butter	Canned seafood	Mouth fresheners
Margarine and fat spreads	Canned meat	Portable sanitary sets
Natural cheese	Canned vegetables	Sanitary products
Processed cheese	Bottled agricultural products	Contraceptives
Yogurt	Bottled seafood	Daily paper products
Cow's milk	Bottled meat	Diapers
Dairy beverages	Bread	Laundry detergent
Lactic acid beverages	Table bread	Kitchenware detergent
Fresh cream	Sweet and steamed Bread	Household cleaners
Soy milk	Cooked bread	Deodorizers, air fresheners and sanitizers
Chilled cool desserts	Cereals	Dehumidifiers
Chilled cakes	Mochi	Insecticides and rat poison
Coffee drinks	Jams	Insect repellents
Cocoa and chocolate beverages	Spreads	Nursing and hygiene products
Tea beverages	Honey and syrups	Denture-related products
Green tea beverages	Dessert mixes	Women's basic cosmetics
Barley tea beverages	Premixes	Women's makeup cosmetics
Oolong tea beverages	Cake and bread ingredients	Women's hair cosmetics
Health tea beverages	Regular coffee	Fragrances
Carbonated soft drinks	Instant coffee	Men's cosmetics
Soft drinks	Drink mixes for cocoa and milk	Cosmetics
Fruit juice 100% beverage	Black tea	Men's hair cosmetics
Vegetable juice	Green tea	Etiquette products
Sports drinks	Barley tea	Razors
Diluted beverages	Oolong tea and health tea	Household medical supplies
Nutritional support drinks	Skimmed milk powder and creaming powder	Baby food supplies
Water	Chocolate	Tobacco and smoking-related products
Nori	Chewing gum	Washroom and bathroom goods
Dried marine products	Candy and candy confections	Laundry and clothes-drying goods
Powders	Snack foods	Cleaning and maintenance supplies
Sesame	Western baked goods	Miscellaneous goods
Dried beans	Dessert cake	Toilet cleaning supplies
Dried agricultural products	Rice crackers	Cooking and kitchenware
Dried noodles	Japanese confectionery	Sink ware
Dried pasta	Japanese cheap candies	Food containers
Sugar and sweeteners	Confectionery with toys	Mops
Salt	Bean confections	Eating utensils
Miso	Fisheries delicacies	Leisure eating supplies
Koji	Livestock delicacies	Durable sink ware
Soy sauce	Nuts	Batteries
Edible vinegar and vinegar-related seasonings	Dried fruits	Stationery and paper products
Mirin and cooking sake	Assorted confectionery	Daily stationery
Edible oil	Sake	Writing supplies
Table sauces	Beer	Painting supplies
Tomato seasoning	Whiskey and brandy	OA supplies
Mayonnaise	Shochu	Documentation supplies
Dressings	Wine	Hooks
Umami seasonings	Liqueurs	Pet sanitary supplies
Instant bouillon	Spirits	Dog food
Spices	Chinese liquor	Cat food
Spices and mixed seasonings	Cocktail drinks	Pet food (excluding dog and cat food)
Sauces	Miscellaneous liquors	Consumable houseware gift sets
Japanese seasonings and sauces	Sparkling wine	
Seasoning sauces	Low alcoholic beverages	

Notes: The shaded area represents the categories of foods.

C. Time Series Properties of Seasonal Component of Price Changes

How important are seasonal components quantitatively relative to variations of the variable in other frequencies? To see this, in Figure C1 we show three measures, all of which are constructed from the estimation results of equation (4) in the main text. The left panel shows variations of seasonal components normalized by the average of the original series for the frequency and size of upward and downward price changes. The height of the bars represents the median of the categories and the error bands indicate the 25th and 75th percentiles of all categories. The center panel shows variations of seasonal components relative to variations of the detrended series. Two observations can be made. The first is that the size of seasonal variations is importantly large and the second is that the seasonal variations are more pronounced in the frequency of price changes than in the size of price changes. The right panel shows the statistical significance of monthly dummies in equation (4), tested using F-tests. Because we execute three-year rolling estimates for each of the series and our sample period ranges from 1990 to 2021, excluding 2003 and 2004, we have at most 36 estimation results for each variable y_{Jt}. For each of the regression results of each of the categories, we test the null hypothesis that "all the coefficients of the monthly dummies, namely a_{Jm} for m=1,…12, are zero," count the share of regression results in which the null hypothesis is rejected at the 5% for each category, and show the median and the 25th and 75th percentiles across the categories. For the frequency of price changes, the null hypothesis is rejected at the 5% level for more than half of the categories for both upward and downward price changes. In contrast, for the size of price changes, the null hypothesis is rejected in around 20% of the regressions, indicating seasonality matters less for the size of price changes.

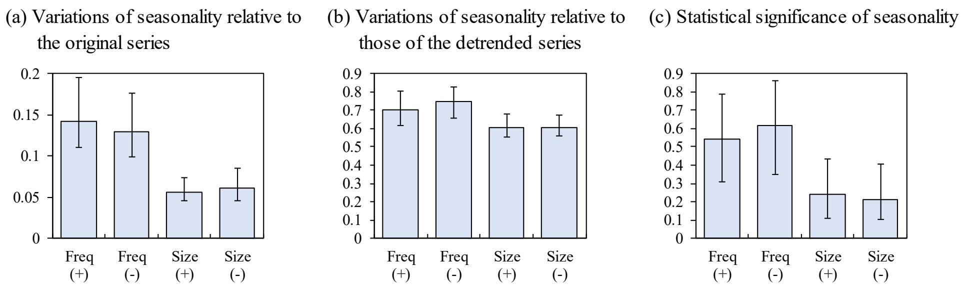

FIGURE C1. IMPORTANCE OF SEASONALITY

Notes: The left and center panels show the across-category distribution of the standard deviation of the seasonal component relative to the average of the original series and to the standard deviation of the detrended series, respectively. The right panel shows the ratio of estimation equations for which the F-test rejects the null hypothesis that the coefficients of the seasonal components are zero at the 95% confidence level. All panels show the median of all categories and the error bands indicate the 25th and 75th percentiles.

D. Seasonality of the Size of Price Changes in More Details

This Appendix examines the degree of synchronization for the size of price changes in a more formal manner than the analysis in Section IV (B) of the main text. In Figure D1, the panels (a) and (b) show the degree of synchronization across categories, represented by the distribution of pairwise correlation coefficients. We compute the correlation of the seasonal components of the size of price changes for every pairwise combination of categories over the sample period for upward and downward price changes separately. It is seen that while a majority of the pairs exhibit positive correlation, the proportion of pairs exhibiting no significant correlation and a negative correlation are not small. For price increases, the median is 0.07 and the peak lies around 0.0-0.1. 7,634 pairs, about 39% of the total number of pairs, show significantly positive correlation at the 5% confidence level and 2,694 pairs, about 14% of the total number of pairs, show significantly negative correlation at the 5% confidence level. For price decreases, the median is 0.08 and the peak again lies around 0.0-0.1. 8,082 pairs, about 41% of the total number of pairs, show significantly positive correlation at the 5% confidence level and 2,729 pairs, about 14% of the total number of pairs, show significantly negative correlation at the 5% confidence level.

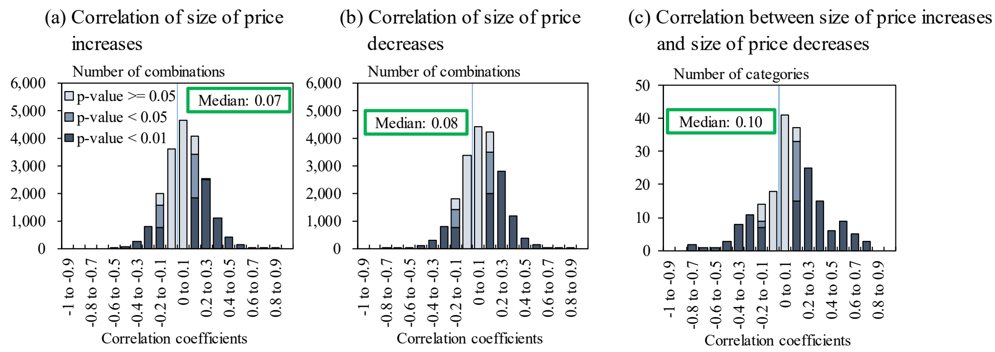

FIGURE D1. CORRELATION OF SIZE OF PRICE CHANGES

Notes: The panel (a) and (b) show histograms of the correlations of the seasonal components of size of price increases and size of price decreases across pairs of 199 categories, respectively. The panel (c) shows histogram of the correlations between the seasonal components of the size of price increases and price decreases within the same category.

The panel (c) shows the degree of the synchronization between price increases and decreases within a category. The median of the correlation is 0.10 and the peak lies around 0.0 to 0.1. Clearly, these numbers are less positive than in the case of the frequency of price changes where, for example, the median is 0.33.

To summarize, while the correlations of the seasonal component of the size of price changes are generally positive both across categories and across the direction, they are less positive than in the case of the seasonal component of the frequency of price changes, indicating that the degree of synchronization is smaller.

E. Stability of Seasonal Component of Price Changes

In order to check the stability of the seasonal patterns of the frequency and size of price changes, we first split the sample period mechanically in half and study how the seasonal patterns in the early and latter halves differ from each other. Figure E1 shows the seasonal patterns of the frequency of price increases (top left panel), that of price decreases (top right panel), the size of price increases (bottom left panel) and that of price decreases (bottom right panel) for the two subsamples for all categories. It can be seen that the general pattern of seasonal components are little changed for the frequency of price changes. The frequency tends to be high in March and September and low in other months. In contrast, the seasonal pattern of the size of price changes is less stable.

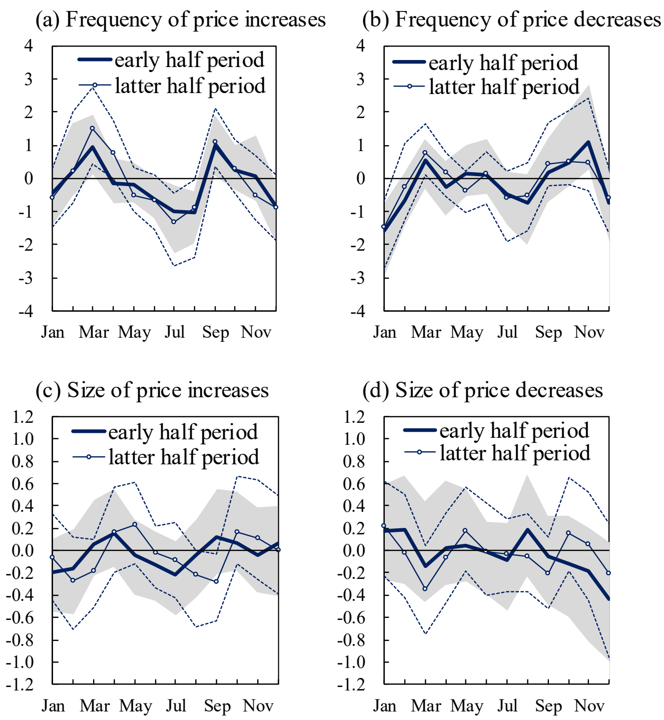

FIGURE E1. SEASONALITY IN THE TWO SUBSAMPLE PERIODS

Notes: The panels plot the average seasonal component in the early and the latter halves of the sample period for each category. The solid line and circle marker indicate the median of all categories. The shaded area and dotted line indicate the 25th and 75th percentile bands.

Figure E2 studies the degree to which the seasonal patterns are stable. For each of the categories, we compute the correlation of the seasonal component in the first half of the sample period and that in the second half of the sample period. The top panels show the correlation for the frequency of price changes. For the frequency of price increases, the median of the distribution across categories is 0.75 and the peak lies around 0.8-0.9. For the frequency of price decreases, the median of the distribution is 0.80 and the peak lies again around 0.8-0.9. The bottom panels show the correlation for the size of price changes. The seasonal pattern is clearly less stable compared with that of the frequency of price changes. For the size of price increases, the median of the distribution is 0.33 and the peak lies around 0.2-0.3, while for the size of price decreases, the median of the distribution is 0.46 and the peak lies around 0.6-0.7 and around 0.8-0.9.

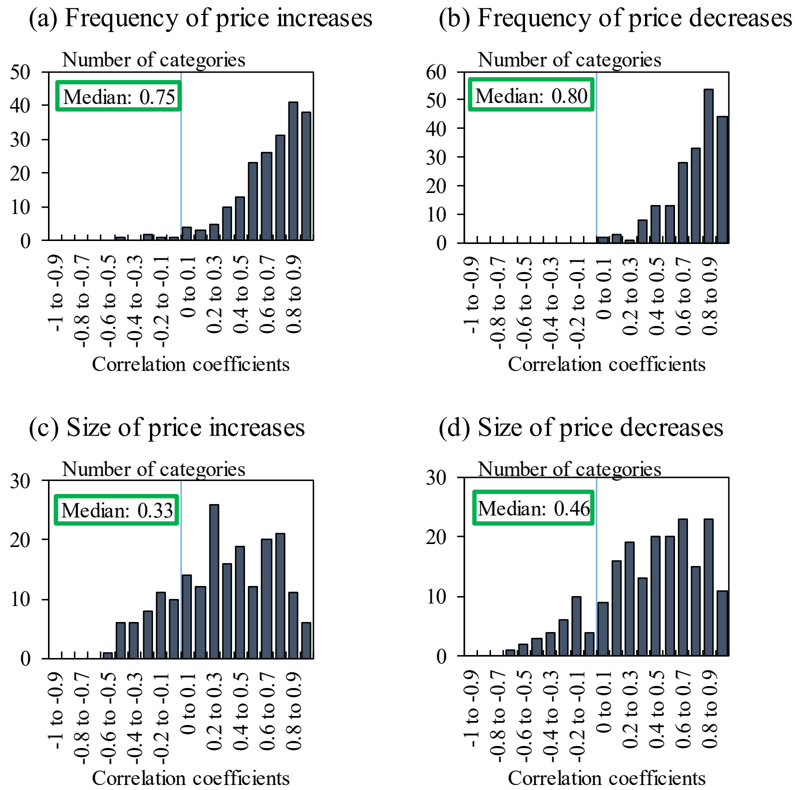

FIGURE E2. CORRELATION OF SEASONALITY BETWEEN THE TWO SUBSAMPLE PERIODS

Notes: These panels show histograms of 199 categories for the correlation of the average seasonal component between the early and latter half of the sample for each series.

F. Characteristics of Seasonal Components extracted by the X12

In the main text, we extract the time series of seasonal components of price dynamics by conducting a rolling estimation of equation (4). In this appendix, as a sensitivity analysis, we use an alternative filter, the X12, to extract the time series of the seasonal components. We then use the X12 filtered seasonal components for the analysis of seasonality of price changes. Compared with the regression-based estimates of seasonal components in our baseline, the seasonal components estimated by X12 filter tend to vary less from year to year.

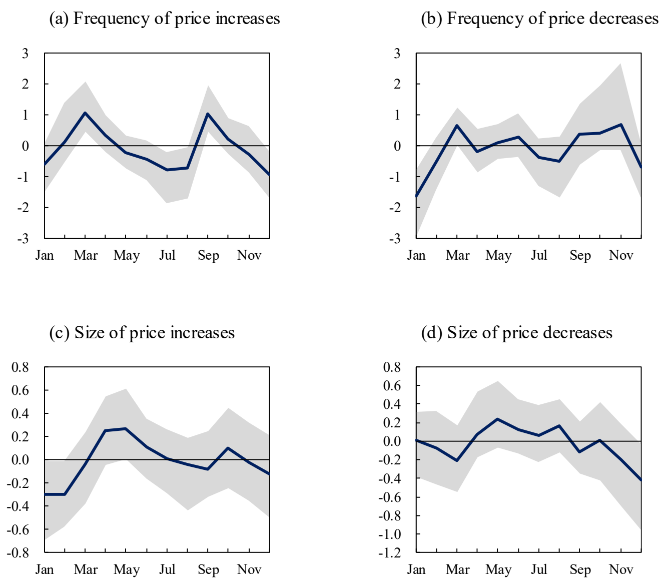

FIGURE F1. SEASONAL COMPONENTS OF PRICE CHANGES EXTRACTED BY X12

Notes: The panels plot the median of the average seasonal component of frequency and size of price changes across all categories. The shaded area indicates the 25th and 75th percentile bands. The seasonal components are extracted by X12.

Figure F1 shows the seasonal components of the frequency and size of price changes for all categories extracted by the X12. Figure F2 shows the correlation between the frequency of price increases and decreases, the correlation between the size of price increases and decreases, and the correlation between the frequency and size of price changes. Figure F3 shows the seasonal component of the POS inflation rate, together with the net frequency and the net size of price changes. Figures F4 and F5 show the seasonal pattern of frequency and size for the high and low inflation periods and the correlation between the standard deviation of the seasonal component of a year of frequency or that of size of price changes with the annual inflation rate of the same year.

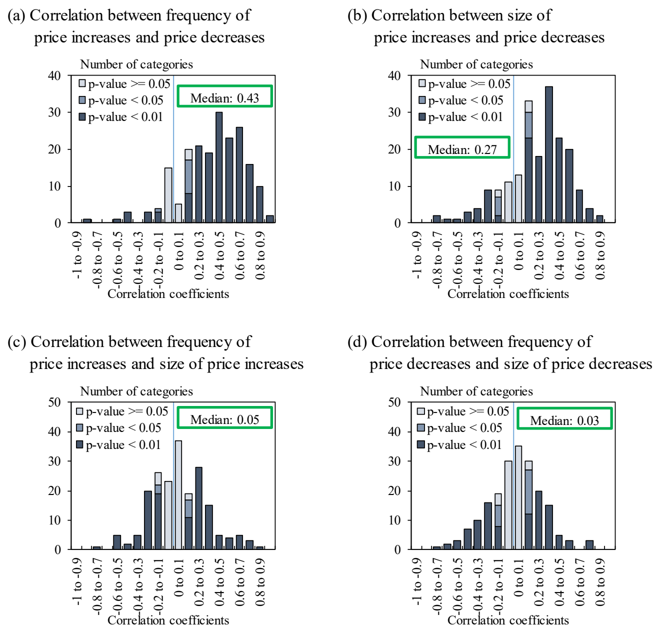

FIGURE F2. CORRELATION OF SEASONALITY OF FREQUENCY AND SIZE OF PRICE CHANGES EXTRACTED BY X12

Notes: The panels show histograms of the correlation between the original series of (a)frequency of price increases and price decreases, (b)size of price increases and price decreases, (c)frequency of price increases and size of price increases, and (d)frequency of price decreases and size of price decreases within the same category. The seasonal components are extracted by X12.

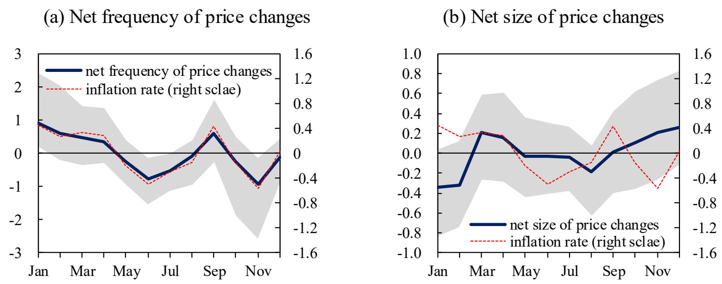

FIGURE F3. SEASONALITY OF NET FREQUENCY AND NET SIZE OF PRICE CHANGES EXTRACTED BY X12

Notes: The panels plot the median of the average seasonal component of net frequency and net size of price changes across all categories. The shaded area indicates the 25th and 75th percentile bands. The seasonal components are extracted by X12.

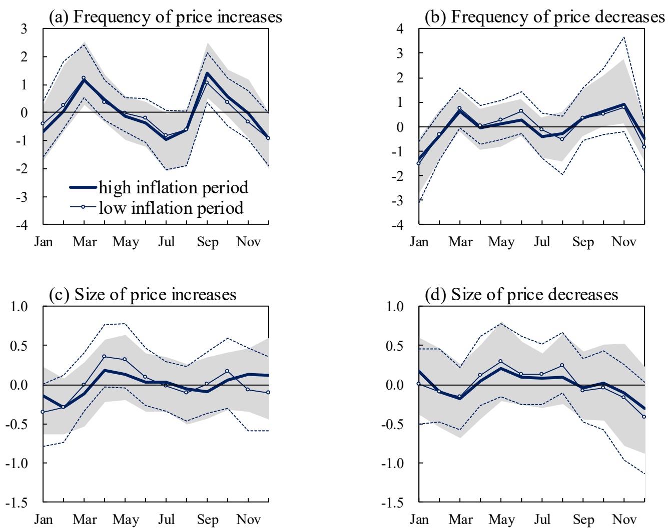

FIGURE F4. SEASONALITY IN HIGH AND LOW INFLATION PERIODS EXTRACTED BY X12

Notes: The panels plot the average seasonal component in the high and the low inflation period for each of the categories. The solid line and that with circle marker indicate the median of all categories. The high inflation period is defined as all years in the top 10% of annual inflation during the whole sample period, and the low inflation period is defined as all years in the bottom 10% for each of the categories. The shaded area and dotted line indicate the 25th and 75th percentile bands. The seasonal components are extracted by X12.

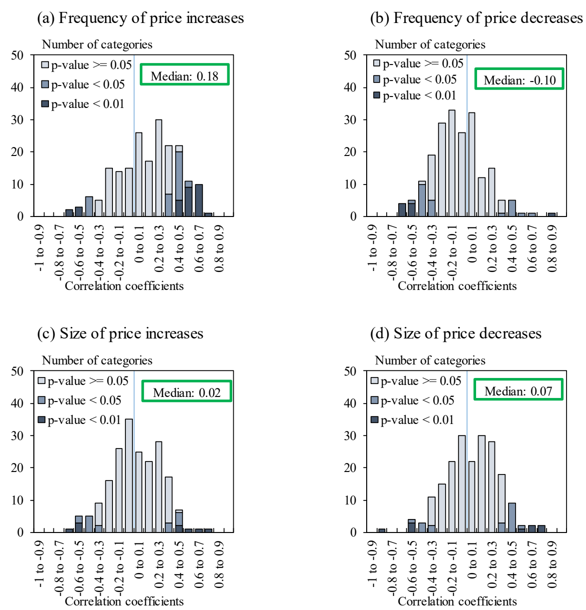

FIGURE F5. CORRELATION BETWEEN ANNUAL POS INFLATION AND SEASONALITY OF PRICE CHANGES EXTRACTED BY X12

Notes: These panels show histograms of the correlation between the annual POS inflation rate and the standard deviation of the seasonal component of (a)the frequency of price increases, (b)the frequency of price decreases, (c)the size of price increases, and (d)the size of price decreases during the year, respectively, for all 199 categories. The seasonal components are extracted by X12.

It can be seen that for the four key observations, three of them hold true for the series extracted by the X12. First, frequencies of both price increases and decreases tend to rise in March and September for most categories, exhibiting a two-humped pattern, with the former more pronounced than the latter. Second, for most categories, seasonal patterns of overall inflation track seasonal patterns of net frequency, i.e., the difference between the frequency of price increases and that of price decreases, and are moderately synchronized across categories. Third, the seasonal patterns of the frequency of price changes of a category have been stable over our sample period but are responsive to annual changes in the inflation rate of the same category for the year. The only exception is the key observation (ii), i.e., the correlation between the frequency and size of price changes. Though the correlation is almost zero for most of the categories, the median of the correlation across categories is positive, contrasting with the results obtained from our baseline series extracted by equation (4) in the main text. The reason for the difference lies in that the seasonal components of a year are computed using a longer window in the X12 compared to our baseline method. For example, while the first several years of the sample from 1990 and 1992 correspond to the period in which the negative correlation between the frequency and size of price changes is the most pronounced, estimated seasonal components of these years are affected by the realizations in the following years when the negative correlation has become smaller.

G. Characteristics of Seasonal Components extracted by Normalizing with the Annual Value

In the main text, we extract the time series of seasonal components by conducting a rolling estimate of equation (4) and study the characteristics of these series. In Appendix F, we show that the three of the four key observations hold for seasonal components extracted by the X12. In this appendix, we use an alternative filter to extract the seasonal components. For a variable y_{Jt}, we divide it by the yearly value, i.e., the average of the 12 monthly values of the same year as the time t, which we denote as $\bar{y}_{Jt}$. The series $y_{Jt}/\bar{y}_{Jt}$ is considered as having had the year effect removed. We then repeat the same empirical exercises as the main text for the series. Compared with our baseline method and X12, one the one hand, the method applied in this appendix allows for flexible changes in seasonal components from year to year. On the other hand, it could recognize idiosyncratic shocks as seasonality, overestimating the variation of seasonality.

Figure G1 shows the correlation between price increases and decreases for the frequency and size of price changes at the top and the correlation between the frequency and size of price changes at the bottom. It can be seen that, as in the analysis in the main text, the seasonal component of the frequency of price increases are positively correlated with that of price decreases and the seasonal component of frequency and size are negatively correlated for both price increases and decreases, indicating that the key observations (i) and (ii) hold for this methodology as well.

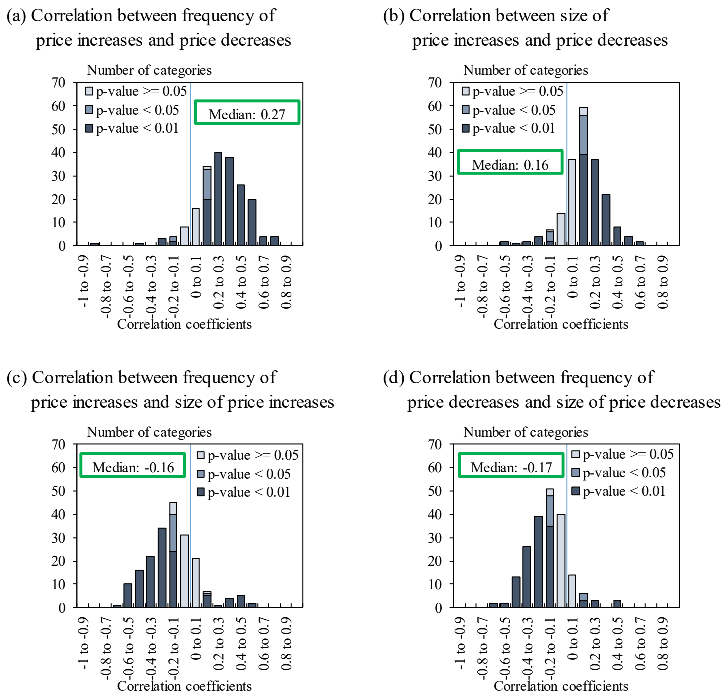

FIGURE G1. CORRELATION OF FREQUENCY AND SIZE OF PRICE CHANGES EXTRACTED BY NORMALIZING WITH THE ANNUAL VALUE

Notes: The panels show histograms of the correlation between the seasonal component of (a)frequency of price increases and price decreases, (b)size of price increases and price decreases, (c)frequency of price increases and size of price increases and (d)frequency of price decreases and size of price decreases within the same category. The seasonal components are extracted by normalizing with the annual value.

Figure G2 shows the correlation between the standard deviation of the seasonal component within a year of a category and the yearly POS inflation rate of the category for the year. It is seen that the seasonal component of the frequency of price changes is responsive to changes in the annual category-level inflation rate for the year in the manner documented in the main text. When the yearly POS inflation is high (low), variations in seasonality becomes high (low), indicating that the key observation (iv) holds.

Figure G3 shows the seasonal component of the POS inflation rate, together with the net frequency and the net size of price changes. It is seen that the key observation (iii) also holds true for the series extracted by the normalizing with the annual value.[2]

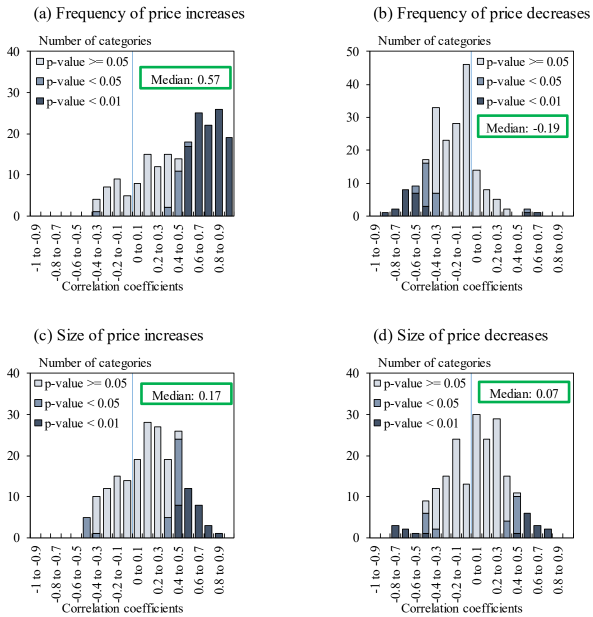

FIGURE G2. CORRELATION BETWEEN ANNUAL POS INFLATION AND SEASONALITY OF PRICE CHANGES EXTRACTED BY NORMALIZING WITH THE ANNUAL VALUE

Notes: These panels show histograms of the correlation between the annual POS inflation rate and the standard deviation of the seasonal component of (a)the frequency of price increases, (b)the frequency of price decreases, (c)the size of price increases, and (d)the size of price decreases during the year, respectively, for all 199 categories. The seasonal components are extracted by normalizing with the annual value.

[2] Because the yearly value $\bar{y}_{Jt}$ of the POS inflation rate and the net frequency could be negative, we subtract it from a variable y_{Jt} instead of dividing for these series.

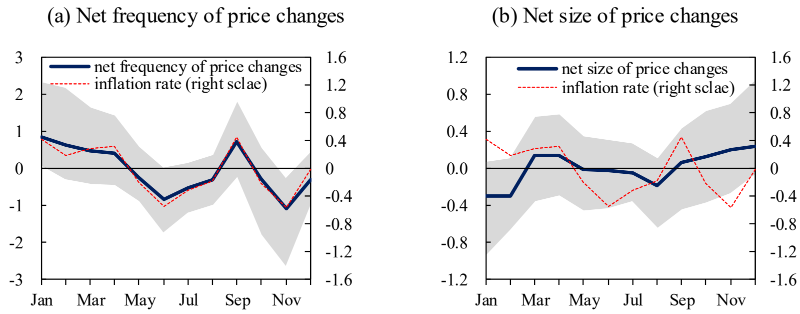

FIGURE G3. SEASONALITY OF NET FREQUENCY AND NET SIZE OF PRICE CHANGES EXTRACTED BY NORMALIZING WITH THE ANNUAL VALUE

Notes: The panels plot the median of the average seasonal component of net frequency and net size of price changes across all categories. The shaded area indicates the 25th and 75th percentile bands. For extracting the seasonal components of net frequency, net size, and inflation rate, we subtract the yearly value from the original series.

H. Degree of Synchronization across Foods and Others

In the main test, we report that the timing of the frequency of price changes is synchronized across different categories. Under the premise that such synchronization arises from implicit coordination among firms, it is likely that similar goods tend to be synchronized more. Our sample category includes 199 categories of goods and there are 145 processed food products and 54 other non-food products as shown in Table B1. In order to see the relation between the degree of synchronization of seasonality of price changes and the degree of similarity among different goods, in this appendix, we divide the sampled 199 categories into two groups "processed food" and "others," and compute the correlation of categories within each of the groups and across the two groups.

Figure H1 shows the degree of synchronization (a) across all categories, (b) within "processed food," (c) within "others," and (d) between "processed food" and "others," for the frequency of price increases. For (b) and (c), we compute the correlation for pairs within the group, and for (d), we compute the correlation for pairs between a category in "processed food" group and a category in "others" group. It is notable that the seasonal components of the frequency of price increases are positively correlated the most for the pairs within “other” and less so for the pairs within “processed food” in terms of the median. The positive correlation also is seen for pairs between the two groups. The median is 0.19 and 12,233 pairs, which is about 62% of the total number of pairs, are significantly positively correlated at the 5% level. The observation that a positive relationship is more pronounced for pairs within the same group rather than for pairs between the groups indicate a possibility that the degree of synchronization may be to some extent affected by the similarity of goods. Figure H2 shows the degree of synchronization for the frequency of price decreases. Again, a positive correlation is obtained for all of the four cases. It is also seen that the correlation is higher for pairs within groups and less so for pairs between groups.

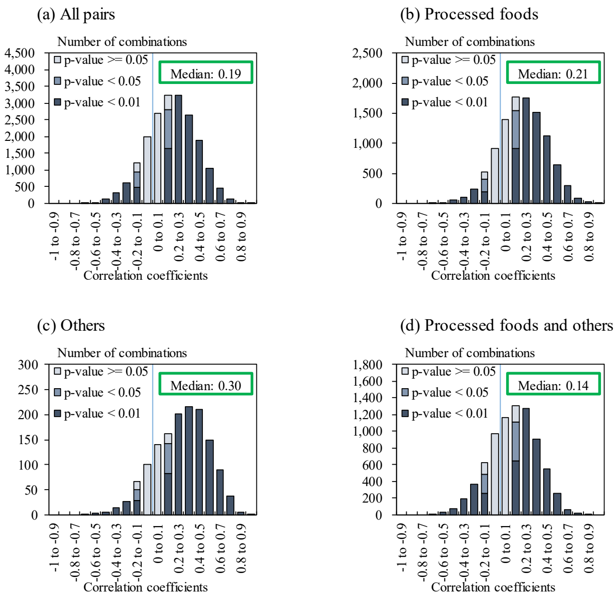

FIGURE H1. CORRELATION OF FREQUENCY OF PRICE INCREASES ACROSS FOODS AND OTHERS

Notes: The panels show histograms of the correlations of the seasonal components of frequency of price increases across pairs of (a)all categories, (b)categories of processed foods, and (c)categories of others, respectively. Panel (d) indicates the correlation between categories of processed foods and those of others. Processed foods include 145 categories and others include 54 categories.

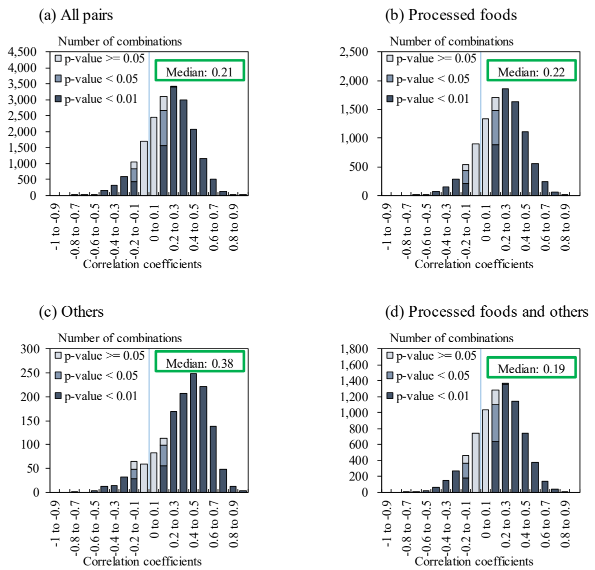

FIGURE H2. CORRELATION OF FREQUENCY OF PRICE DECREASES ACROSS FOODS AND OTHERS

Notes: The panels show histograms of the correlations of the seasonal components of frequency of price decreases across pairs of (a)all categories, (b)categories of processed foods, and (c)categories of others, respectively. Panel (d) indicates the correlation between categories of processed foods and those of others. Processed foods include 145 categories and others include 54 categories.

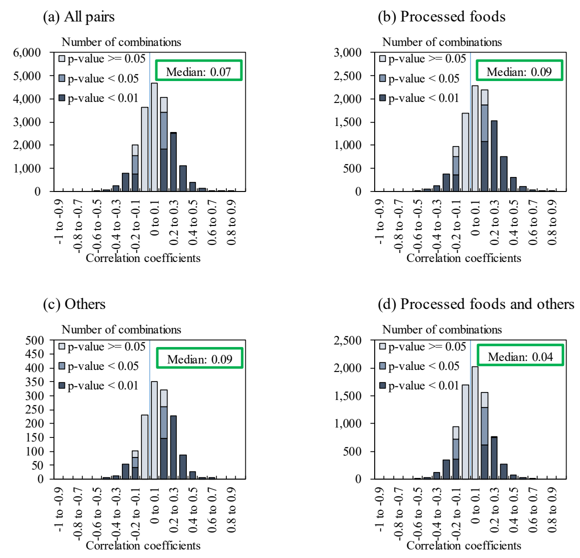

FIGURE H3. CORRELATION OF SIZE OF PRICE INCREASES ACROSS FOODS AND OTHERS

Notes: The panels show histograms of the correlations of the seasonal components of size of price increases across pairs of (a)all categories, (b)categories of processed foods, and (c)categories of others, respectively. Panel (d) indicates the correlation between categories of processed foods and those of others. Processed foods include 145 categories and others include 54 categories.

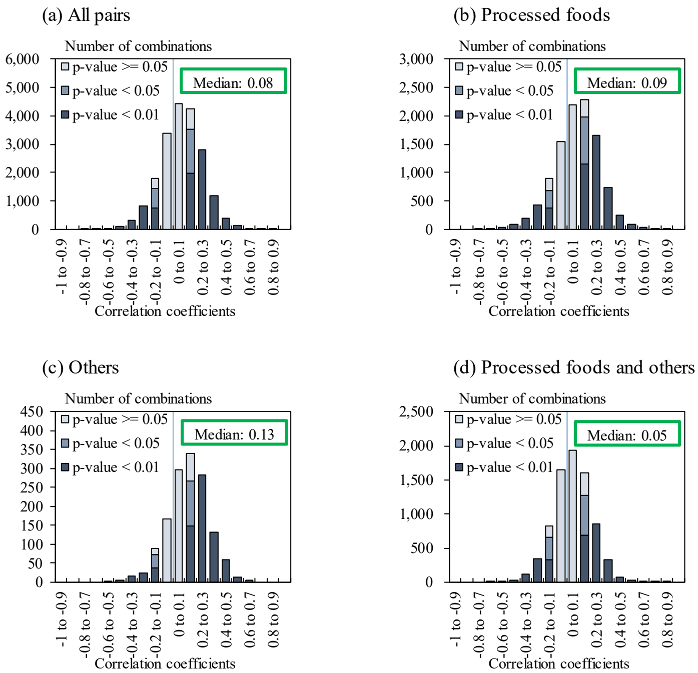

FIGURE H4. CORRELATION OF SIZE OF PRICE DECREASES ACROSS FOODS AND OTHERS

Notes: The panels show histograms of the correlations of the seasonal components of size of price decreases across pairs of (a)all categories, (b)categories of processed foods, and (c)categories of others, respectively. Panel (d) indicates the correlation between categories of processed foods and those of others. Processed foods include 145 categories and others include 54 categories.

Figures H3 and H4 show the case for the size of price changes. Compared with the frequency of price changes, the correlation is muted for both within and between groups.

I. Number of Statistically Significant Monthly Dummies

In the main text, we measure the size of seasonality with the size of the coefficients of monthly dummies in equation (4). Based on the measure, we show that the frequency of price changes has two peaks, rising in March and September and falling in June and that the size of price changes does not have salient seasonal patterns. In this appendix, we focus on the statistical significance of the coefficients of monthly dummies in equation (4) and show that similar observations can be made.

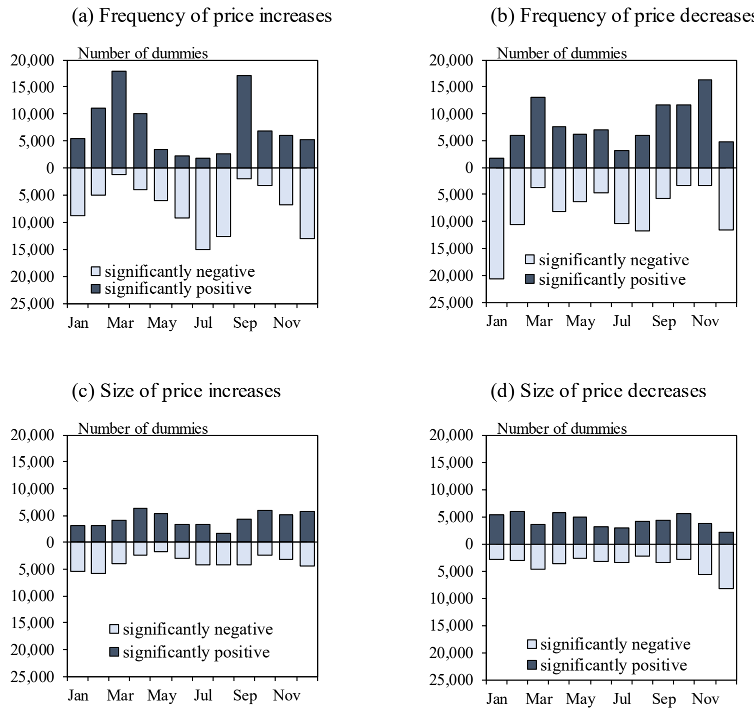

FIGURE I1. NUMBER OF STATISTICALLY SIGNIFICANT MONTHLY DUMMIES (1)

Notes: These panels show the number of statistically significant dummies in the estimation of equation (4). Dummies are estimated using a three-year rolling estimation for each of the 199 categories. For each category, there are about 300 coefficients on the dummies and overall there are 57,362. The bars represent the number of dummies that are statistically significant at the 95% confidence level.

Figure I1 shows the number the number of statistically significant dummies in the estimation of equation (4) for the frequency of price changes at the top and for the size of price changes at the bottom. The x-axis is month and the y-axis is the number of dummy variables that are different from zero at 95% statistical significance. Note that because the dummies are estimated with a three-year rolling estimation for each of 199 categories, there are 57,362 estimates. It is seen that the two months with the highest number of statistically significant positive dummy variables are March and September and the two months with the highest number of statistically significant negative dummy variables are July and December for the frequency of upward price changes. For the frequency of downward price changes, the two months with the highest number of statistically significant positive dummy variables are March and November and the two months with the highest number of statistically significant negative dummy variables are January and August for the frequency of upward price changes. For the size of price changes, the number of dummies that are statistically significantly different from zero is far moderate and the difference of the number of such dummies across months is less pronounced relative to the frequency of price changes.

Figure I2 shows the case when the dummies are estimated based on the full-sample period instead of a three-year rolling estimation. The similar observations can be made to those shown in Figure I1.

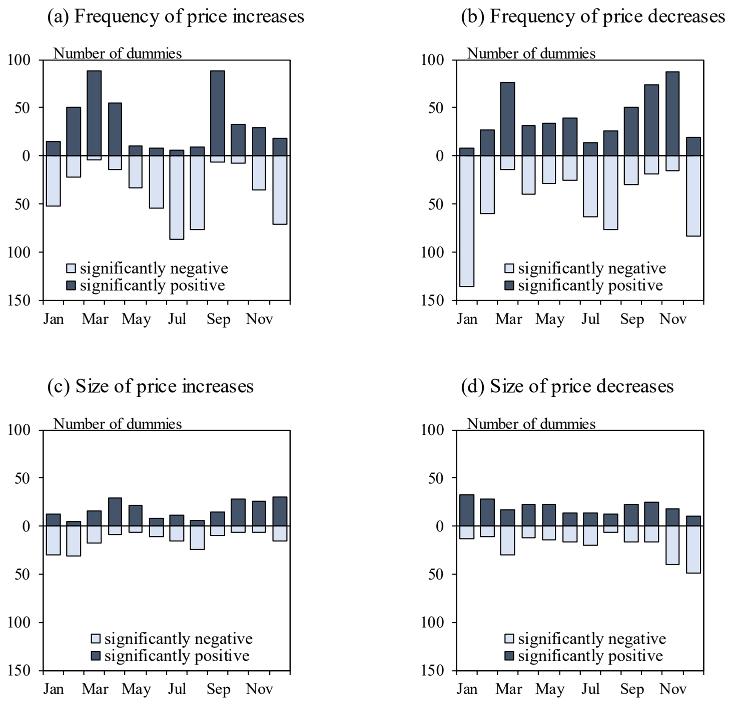

FIGURE I2. NUMBER OF STATISTICALLY SIGNIFICANT MONTHLY DUMMIES (2)

Notes: These panels show the number of statistically significant dummies in the estimation of equation (4). The dummies are estimated based on the full-sample period instead of a three-year rolling estimation and there are 12 dummy variables for each of 199 categories. The number of dummies that are statistically significant at the 95% confidence level is reported.

REFERENCES

Abe, N., A. Tonogi (2010) “Micro and Macro Price Dynamics in Daily Data,” Journal of Monetary Economics, 57(6), pp. 716--728.

Nakamura, E., J. Steinsson (2008) “Five Facts About Prices: A Reevaluation of Menu Cost Models,” Quarterly Journal of Economics, 123(4), pp. 1415--1464.

Nakamura, E., J. Steinsson (2010) “Monetary Non-Neutrality in a Multi-Sector Menu Cost Model,” Quarterly Journal of Economics, 125(3), pp. 961--1013.

Sudo, N., K. Ueda, K. Watanabe (2014) “Micro Price Dynamics during Japan's Lost Decades,” Asian Economic Policy Review, 9(1), pp. 44--64.

Sudo, N., K. Ueda, K. Watanabe, T. Watanabe (2018) “Working Less and Bargain Hunting More: Macro Implications of Sales during Japan's Lost Decades,” Journal of Money, Credit and Banking, 50(2-3), pp. 449--478.

Ueda, K., K. Watanabe, T. Watanabe. 2019. “Product Turnover and the Cost-of-Living Index: Quality versus Fashion Effects.” *American Economic Journal: Macroeconomics*, 11(2): 310–347.