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

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

Seasonality is among the most salient features of price changes, but it is notably less analyzed than seasonality of quantities and the business cycle component of price changes. To fill this gap, we use the scanner data of 199 categories of goods in Japan to empirically study the seasonality of price changes from 1990 to 2021. We find that the following four features generally hold for most categories: (1) The frequency of price increases and decreases rises in March and September; (2) Seasonal components of the frequency of price changes are negatively correlated with those of the size of price changes; (3) Seasonal components of the inflation rate track seasonal components of net frequency of price changes; (4) The seasonal pattern of the frequency of price changes is responsive to changes in the category-level annual inflation rate for the year. We use simple state-dependent price models and show seasonal cycles in menu costs play an essential role in generating seasonality of price changes.

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I. Introduction

It is widely known among both scholars and policymakers that the time series of prices have a sizable degree of seasonality. Figure 1 shows the decomposition of the yearly growth rate of the CPI, for all items and for goods less fresh food and energy, into twelve month-to-month changes within the same year in Japan. It can be seen that there are months in which prices generally increase, such as March and April, and months in which prices generally decrease, such as January and February. Such seasonal patterns have been stable from the 1990s to 2020s.

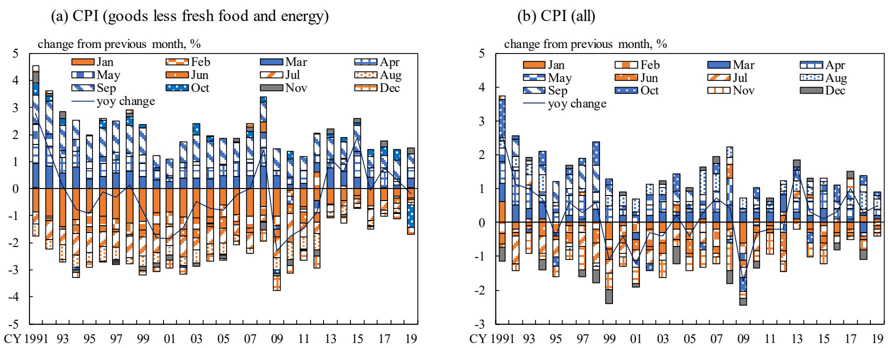


FIGURE 1. DECOMPOSITION OF THE ANNUAL CPI CHANGE IN JAPAN

Notes: The figures are adjusted for changes in the consumption tax rate in 1997, 2014, and 2019.

These seasonal patterns of price changes have attracted the attention of macroeconomists and the presence of seasonal patterns itself has been documented in a good number of existing studies in the literature of macroeconomics. For example, a seminal paper by Nakamura and Steinsson (2008) points out that the frequency of price changes tends to be the highest in the first quarter and declines monotonically through the fourth quarter for consumer prices and states "seasonality of the frequency of price change" as one of the five noteworthy facts regarding price dynamics in the U.S. Despite drawing attention to these facts, these studies do no more than report the existence of seasonal patterns and do not make these facts the central focus of their analysis.[1] Consequently, there remain issues that are not fully analyzed regarding the seasonality of price changes.

We aim to fill this gap by answering three questions: What are the key features of the seasonality of price changes? What types of economic structures are consistent with the observed features? What are the macroeconomic implications of seasonality of price changes? To this end, we conduct empirical and theoretical analyses. For the empirical analysis, we study the seasonality of price changes from January 1990 to December 2021 using scanner data in Japan. The data contain about 11 billion observations of food and daily commodities, except for fresh food. We decompose the inflation rate into frequency and size for upward price changes and downward price changes following Klenow and Kryvtsov (2008), extract the seasonal components of these series, and study their characteristics in details.

For the theoretical analysis, we build simple menu cost models and examine what model features are needed to bring the model close to the observed features of the data. Regarding the causes of the seasonality of price changes, Olivei and Tenreyro (2010) stress the importance of differences in wage flexibility across different months of the year. Nakamura and Steinsson (2008) point out the role of time-dependency in price setting. We address these two views in our exercise. We simulate three models, two of which assume seasonal changes in real wages while the other assumes seasonal changes in menu costs. We then compare which of the three models can successfully generate seasonal patterns of price changes seen in the data.

Our findings can be summarized as follows. Regarding the empirical analysis, we observe four key features. First, the frequency of price increases and decreases tends to rise in March and September for most categories. In other words, the timing

[1] This contrasts with seasonality of quantity, which has been taken as the main theme and central subject of analysis in macroeconomics. See, for example, the pioneering work by Barsky and Miron (1989).

of price changes coincides within a category and across categories as well as for both upward and downward price changes. Second, for the majority of categories, seasonal components of the frequency of price changes are negatively correlated with those of the size of price changes. Third, the seasonal patterns of the inflation track the seasonal patterns of net frequency, i.e. the difference between the frequency of price increases and price decreases, and are moderately synchronized across categories. Fourth, the seasonal pattern of the frequency of price changes is responsive to changes in the annual category-level inflation rate for the year. That is, the seasonal component of the frequency of price increases (decreases) of a category becomes more volatile (less volatile) when the category-level annual inflation rate for the year is high (low). In other words, a rise in the frequency of price increase in March and September of a category becomes more pronounced when the inflation rate of the category for the year is high. Such responses are not seen in the seasonal component of the size of price changes.

Our theoretical analysis shows that seasonal cycles in menu costs, i.e., declines in March and September, are needed to bring the model close to the observations. Indeed, the model with seasonal cycles in menu costs is able to produce the four features qualitatively. First, under the assumption that menu costs are low in March and September, firms face an added incentive to change their prices for both upward and downward price changes. Consequently, the frequency of both price increases and decreases becomes high in these two months compared with other months. Second, because a larger portion of firms, including those whose prices are not very far from the target price, changes their prices in the two months, the average size of price changes falls, yielding a negative correlation between the frequency and the size of price changes. Third, as seasonal cycles of menu costs generate larger seasonal variations in frequency rather than those in size, the seasonal patterns of net frequency trace those of the inflation rate. Forth, the seasonal pattern of the frequency of price increases (decreases) becomes more (less) pronounced as the steady-state inflation rate rises, since a larger (smaller) portion of firms finds it necessary to change their prices.

Our paper contributes to the literature on price dynamics in three aspects. First, it empirically uncovers characteristics of seasonality of price changes that have been unexplored in detail in existing studies. For example, to the best of our knowledge, the relationship between the seasonal components of the size and frequency of price changes and the responsiveness of seasonal patterns of price changes to the annual inflation rate for the year have not been studied.[2] Second, our paper offers a theoretical explanation as to why there are such seasonal patterns by using a state-dependent pricing model. While existing studies such as Álvarez et al. (2006) and Nakamura and Steinsson (2008) document the presence of seasonality and discuss the potential sources of the seasonality, they do not explicitly construct a model that accounts for the seasonal patterns. Third, our result that there are seasonal cycles in menu costs underscore the importance of the "month" in macroeconomic dynamics. For example, because there are months in which price changes are likely to occur and months they are not, the transmission of shocks to output and prices is considered as being affected by the months in which the original shocks occur. This point is, in fact, consistent with the argument made by Olivei and Tenreyro (2010) that monetary policy transmission to goods and prices is affected by the month in which monetary policy shocks occur.

In addition, our finding regarding the seasonal cycles of menu costs provides insights into the nature of menu costs. The feature that menu costs fall in a specific month in a synchronized fashion across different categories agrees with the arguments made in early works by Zbaracki et al. (2004) and Blinder et al. (1998).

[2] The characteristics of the frequency and size of price changes, including their relationships with the annual inflation rate, have already been investigated in existing studies, such as Klenow and Kryvtsov (2008) and Blanco et al. (2024), using original data and seasonally adjusted data. Blanco et al. (2024), for example, documents that the frequency of price changes increases from 10% to 14% when the sectoral inflation rate increases from around zero to 5% in the original data from the United Kingdom Office for National Statistics. However, these studies do not analyze the seasonal components themselves.

Using data from a large U.S. industrial manufacturer and its customers, Zbaracki et al. (2004) documents that in addition to physical menu costs there are three types of managerial costs—information gathering, decision making and communication costs, and two types of customer costs—communication, and negotiation costs. Blinder et al. (1998), based on a survey of firms in the U.S., documents that an important portion of firms indicate coordination failure as a potential theory for price stickiness. One potential interpretation of the seasonal cycles of menu costs is that, due to commonly held expectations by firms, there is implicit coordination among firms in specific months, so that the non-physical components of menu costs, such as those associated with communication and negotiation, decline in these months.

The structure of this paper is as follows. Section II overviews the literature. Section III explains the scanner data. Section IV provides stylized facts on the seasonality of price changes. Section V develops a menu cost model that provides explanations for the seasonality of the changes. Section VI concludes.

II. Literature Review

Our study is related to two strands of literature. The first strand of studies includes works that focus on seasonality of macroeconomic variables. Almost all of these works focus on quantity variables. Seminal works by Barsky and Miron (1989) and Miron (1996) show that, for example, for GDP and its components, seasonal variations are sizable and that seasonal cyclicality of these variables resembles business cycle variations in various dimensions, including co-movement of the variables. From a slightly different angle, Beaulieu et al. (1992), Cecchetti and Kashyap (1996) and Matas-Mir and Osborn (2004) study interactions between seasonal cycles and business cycles.[3] Olivei and Tenreyro (2010) compare the estimated response of industrial goods production to a monetary policy shock across selected developed countries, including Japan, and show that in Japan monetary policy shocks that occur in the first quarter yield a muted impact on output compared with shocks that occur in the third quarter of a year. They argue that this is because the re-negotiation of wages tends to take place in a good number of firms during the annual wage negotiations, known as Shunto, that occur in the first and second quarters in Japan. Our paper is related to Cecchetti and Kashyap (1996) and Matas-Mir and Osborn (2004) in the sense that it provides a potential channel that generates interactions between seasonal and business cycles in price dynamics. As in the data, with seasonal cycles in menu costs, our model predicts a larger increase (a muted increase) in the frequency of price increases (price decreases) when the inflation rate of the category is high. Our paper is related to Olivei and Tenreyro (2010) in the sense that it offers an alternative explanation for their empirical finding. Namely, both their paper and our paper emphasize that a monetary policy shock is affected by the month in which it occurs, though they stress the importance of changes in wage flexibility and our paper stresses the role of changes in the size of menu costs across months.

The second strand of studies includes works on macroeconomic price dynamics that exploit granular data, including scanner data. These studies particularly focus on the distinction between the intensive and extensive margins of price changes behind price stickiness, i.e., the size and frequency of price changes, and explore whether or not the data agree with the implications of models used in the literature

[3] Cecchetti et al. (1997) also show that, in several U.S. industries, economic booms are associated with a reduction in the seasonal variations of production and either no change or an increase in the inventories during the high-production season. Based on this findings, they conclude that firms in these industries face upward-sloping and convex marginal-production-cost curves. Krane and Wascher (1999) investigate interactions between seasonal and cyclical movements in U.S. payroll employment using a multivariate unobserved components model, and find statistically significant interactions in a number of industries. Geremew and Gourio (2018) present some stylized facts about seasonality in U.S. employment and argue that seasonality has rarely associated with cyclicality contrasting to earlier studies.

of macroeconomics, such as the Taylor model, Calvo model, and state-dependent pricing model. These works include, for example, Levy et al. (1997), Bils and Klenow (2004), Klenow and Kryvtsov (2008), and Nakamura and Steinsson (2008). A good survey is conducted by Mackowiak and Smets (2009), Klenow and Malin (2010), and Nakamura and Steinsson (2013). There are also studies that exploit granular data and study Japan's micro price dynamics. Such works include the Bank of Japan (2000), Higo and Saita (2007), Ikeda and Nishioka (2007), Mizuno et al. (2010), Abe and Tonogi (2010), Watanabe and Watanabe (2014), Sudo et al. (2018), and Ueda et al. (2019). In terms of the data, our data is the same as that used in Abe and Tonogi (2010), Sudo et al. (2018), and Ueda et al. (2019), though our data set is longer than theirs. Our paper is similar to some of these studies in the sense that it empirically studies the intensive and extensive margins of price changes and theoretically examines if the data findings are consistent with the implications of a state-dependent pricing model. However, our paper differs starkly from these studies in focusing on the seasonal components of price changes.

As discussed above, seasonality itself is already documented, for example, in Nakamura and Steinsson (2008) and Álvarez et al. (2006), and Bunn and Ellis (2012). In contrast to our study, however, the seasonality is not the central focus of these studies. Consequently, they do not formally extract the seasonal component of price changes nor study causes of seasonality using a theoretical model.

III. Data and Definition of Variables

A. Data

We employ 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. In our analysis on prices, we use unit price calculated by dividing the sales by the number of units sold for each product i 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.[4]"

B. Regular Prices

We focus on regular prices, excluding sales, following existing studies such as Nakamura and Steinsson (2008). We use a mode filter to obtain the regular prices, as in Abe and Tonogi (2010) and Eichenbaum et al. (2011). Namely, the regular

[4] We exclude from our analysis the data of years and categories for which the sampled data are partly missing. Consequently, we use the data of 199 categories out of 217 categories from the beginning of January 1990 to the end of December 2021 for our analysis. The details of the data description including these adjustments and the list of categories studied in this paper are reported in Online Appendix B.

price of a product at a particular date is defined as the mode of the daily prices of the product within a window of 89 days i.e., between 44 days before and 44 days after the day of measurement.

C. Definition of Variables

Following Klenow and Kryvtsov (2008), we decompose the inflation rate into the frequency of price changes and the size of price changes. In addition, for both the frequency and size of price changes, we further separate upward and downward changes. More precisely, the regular price inflation of category J in month t, which is expressed as π_{Jt}, can be decomposed into the following four elements.

$$\pi_{Jt} = FREQ_{Jt}^{+}SIZE_{Jt}^{+} - FREQ_{Jt}^{-}SIZE_{Jt}^{-} \quad (1)$$

Here, the frequency of upward (downward) price adjustment of category J in month t, which is expressed as $FREQ_{Jt}^{+}$ ($FREQ_{Jt}^{-}$), is given as the number of products i that belong to category J and have changed their price upwards (downwards) on any day d in the month divided by the total number of products i that belong to category J, as described in the equation below.

$$FREQ_{Jt}^{\pm} = \frac{\sum_{i \in J,\, d \in t} 1(p_{id} \gtrless p_{id-1})}{\sum_{i \in J, d \in t}[1(p_{id} > p_{id-1}) + 1(p_{id} = p_{id-1}) + 1(p_{id} < p_{id-1})]} \quad (2)$$

When the regular price of a product on a day does not differ by more than 3 yen from the previous observation, we regard the regular price as having remained unchanged.[5] This 3-yen rule follows Sudo et al. (2014) and is motivated by the

[5] In equation (2), we compute the frequency of price changes using changes from the previous day. In the analysis below, because we focus on the monthly difference, we construct the monthly frequency of price changes from the daily frequency of price changes using the formula $FREQ_{Jt}^{\pm}(monthly) = 1 - \left(1 - FREQ_{Jt}^{\pm}\right)^{30}$ for all months. We use 30 instead of the actual number of days for each month, such as 29 for February and 31 for January, in order to control the effects of the length

observation that some products have non-integer unit prices after dividing the sales by the number of units sold. The non-integer unit prices may arise due to various factors, such as time sales within a day, buy-one-get-one-free sales, and the artifact that arises when the reported sales include the consumption tax and Nikkei Digital Media removes the effect of the tax by dividing the reported sales by the tax rate.

Similarly, the size of the upward (downward) price adjustment of category J in month t, which is expressed as $SIZE_{Jt}^{+}$ ($SIZE_{Jt}^{-}$) is given as the size of the price change of product i whose price is changed upward (downward) on any day d in the month divided by the total number of products i that belong to category J whose price has changed upward (downward) as described in the equation below.

$$(3) \qquad SIZE_{Jt}^{\pm} = \frac{\sum_{i \in J,\, d \in t} |log(p_{id}/p_{id-1})| 1(p_{id} \gtrless p_{id-1})}{\sum_{i \in J,\, d \in t} 1(p_{id} \gtrless p_{id-1})}$$

D. Seasonality

To measure the seasonality for each category-level variable of interest y_{Jt}, i.e., the frequency and size of price adjustments, we estimate the equation below for each of these variables, following Geremew and Gourio (2018).[6]

$$(4) \qquad y_{Jt} = \sum_{m=1}^{12} \left(a_{Jm} dum_{m,t}\right) + \beta_{J0} + \beta_{J1} \times t + \beta_{J2} \times t^2 + \epsilon_{Jt} \,,$$

of the month. The results are little changed, however, if the actual number of days is used instead of 30 when constructing the monthly frequency of price changes.

[6] We use as the baseline the seasonal components of variables extracted from equation (4) throughout our analysis as they are simple and easily interpretable. For the purpose of robustness checking, however, we study seasonal components obtained by two other methodologies as well. In Online Appendix F, we show the results when we use X12 for extracting seasonal components from the original series to analyze seasonal patterns. In Online Appendix G, we show the results when we normalize the original series with the average of the value of twelve months in the same year. In both of the methodologies, most of the results are barely changed for the four key observations.

$$subject\ to\ \sum_{m=1}^{12} a_{Jm} = 0,$$

where $dum_{m,t}$ is a dummy variable that takes one when time t occurs in month m and zero otherwise. The coefficient a_{Jm} captures the effect of a particular month m. The coefficients β_{J1} and β_{J2} capture the effects of a linear trend and a quadratic trend, respectively.[7] We estimate the above equation using rolling regressions with a three-year window allowing seasonality to change over time. The size of seasonality for a specific year y is obtained by taking the average of the estimates of the rolling regressions whose sample period includes year y.[8]

IV. Observations

This section documents characteristics of the seasonal component of price changes based on our scanner data. In summary, there are four key observations.

(i) For most categories, the frequency of both price increases and decreases tends to rise in March and September, exhibiting a two-humped pattern.

(ii) For the majority of categories and for both price increases and decreases, the seasonal components of the frequency of price changes are negatively correlated with those of the size of price changes.

[7] While Geremew and Gourio (2018) use the Hodrick-Prescott filter to remove the trend, we use the linear and quadratic trend dummies because there are missing observations in our data and the Hodrick-Prescott filter cannot be applied.

[8] In Online Appendix C, we compare a relative significance of seasonal cycle component and that of other components for frequency and size of price changes. We show that the size of seasonal variations is importantly large relative to other variations for both the frequency and size of price changes though the seasonal variations are more pronounced in the frequency of price changes than in the size of price changes.

(iii) For most categories, the seasonal component of the overall inflation rate tracks the seasonal component of net frequency, i.e., the difference between the frequency of price increases and that of price decreases.

(iv) The seasonal pattern of the frequency of price changes has been responsive to changes in the category-level annual inflation rate for the year. That is, the seasonal component of the frequency of price increases (decreases) becomes more (less) volatile when the category-level inflation rate is high.

We focus our analysis on the seasonal components extracted by the methodology described in equation (4). Unless otherwise noted, all of the analysis below are those of the seasonal components rather than those of the original series.

A. Seasonality of the Frequency of Price Changes

The panel (a) of Figure 2 shows the seasonal components of the frequency of price changes, averaged over the entire sample year, for the category "tofu," and the panels (b) show the corresponding seasonal components for all categories. The solid and dotted lines in the panels (b) represent the median and the shaded area represents the 25th-75th percentile bands across categories.

There are two points worth noting. First, for "tofu," there are noticeable seasonal patterns for both upward and downward price changes. The frequency is high in March and September and low in other months for both price changes. Second, similar seasonal patterns are observed for all categories, which implies that the synchronization is present not only between directions but also across categories.

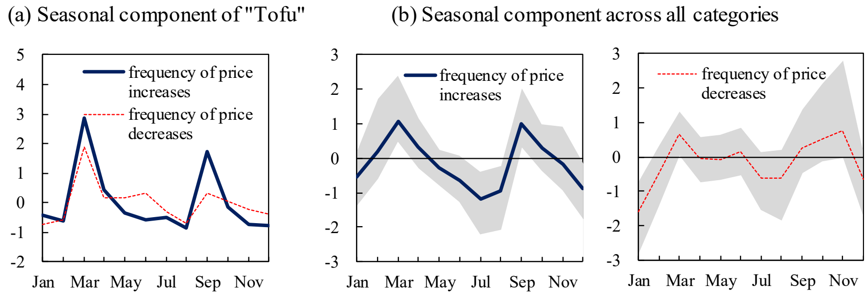


FIGURE 2. FREQUENCY OF PRICE CHANGES

Notes: The left panel plots the seasonal components of the frequency of price increases and price decreases averaged over the entire sample year for the category "soybean curd and its products, Tofu." The middle and right panels plot the median of the corresponding seasonal components across all categories. The shaded area indicates the 25th and 75th percentile bands.

Figure 3 studies formally the degree of synchronization across categories and across directions. The panels (a) and (b) show the distribution of pairwise correlation coefficients across categories. We compute the correlation of the seasonal components of the frequency of price increases and decreases for every 19,701 (199 times 198/2) pairwise combination of categories. The seasonal components of the frequency of price changes are generally positively correlated for most of the pairs. For price increases, the peak lies around 0.1-0.2 and the median is 0.19. 12,233 pairs, about 62% of the total number of pairs, are significantly positively correlated at the 5% confidence level. For price decreases, the peak lies around 0.2-0.3 and the median is 0.21. 12,975 pairs, about 66% of the total number of pairs, are significantly positively correlated at the 5% confidence level.

The panel (c) shows the synchronization across directions. We compute the correlation of the two time series, i.e., the seasonal components of the frequency of price increases and decreases, for each of the 199 categories. For most categories, the frequency of upward and downward price changes of a category are positively correlated. Namely, the median of the correlations is 0.33 and the peak lies around 0.3-0.4[9].

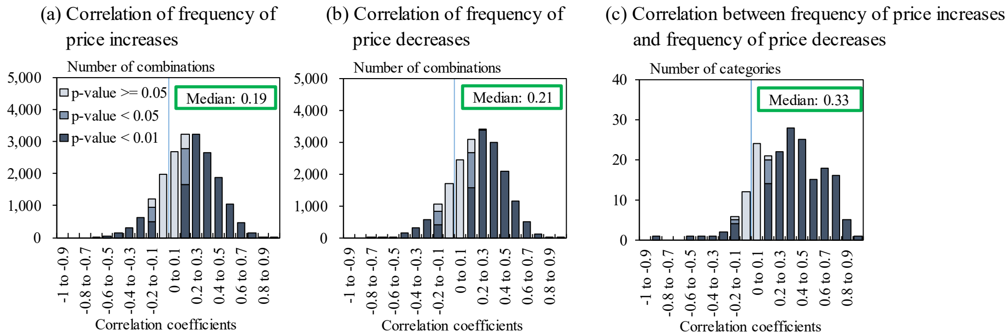


FIGURE 3. CORRELATION OF FREQUENCY OF PRICE CHANGES

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

B. Seasonality of the Size of Price Changes

The panel (a) of Figure 4 shows the seasonal components of the size of price changes, averaged over the entire sample year, for the category "tofu," and the panels (b) show the corresponding seasonal components for all categories. The solid and dotted lines in the panels (b) represent the median and the shaded area represents the 25th-75th percentile bands across categories.

For both price increases and decreases, it is not obvious that seasonal variations of size of price changes are synchronized across categories and/or across directions. For the category "tofu," the size of price changes tends to be large in January, November, and December and tends to be small in March and around September for both price increases and decreases. This observation, however, does not hold as

[9] In this paper, we use Pearson's correlation when examine the relationship between the two variables. While we do not show for the purpose of saving the space, we conduct the same exercise using Spearman's rank correlation instead of the Pearson's correlation as a robustness check and obtain qualitatively similar results.

clearly for other categories. In fact, differences in the size of price changes across months are less visible compared with the case of the frequency of price changes. Online Appendix D shows the degree of synchronization for the size of price changes across categories and across directions in a more formal manner.

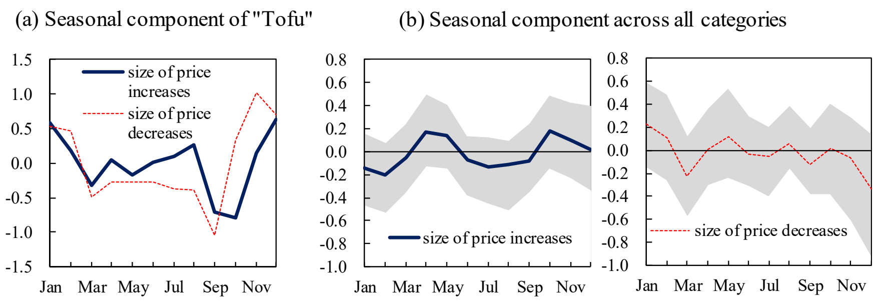


FIGURE 4. SIZE OF PRICE CHANGES

Notes: The left panel plots the average seasonal component of the size of price increases and price decreases of the category "soybean curd and its products, Tofu." The middle and right panels plot the median of the average seasonal component of size of price changes across all categories. The shaded area indicates the 25th and 75th percentile bands.

How are the seasonal components of the size of price changes related to those of the frequency? For the category "tofu," Figure 2(a) and 4(a) imply that there is a negative correlation between the seasonal components of the frequency and the size of price changes. To see this in other categories, we compute the correlation between the seasonal components of the frequency and size of price changes for each of the categories. The panel (a) in Figure 5 shows the distribution across categories of the correlation between the frequency and the size of price increases. The seasonal components of the frequency and size of price increases are negatively, though modestly, correlated. The median of the correlation is -0.11 and the peak lies around -0.2 to -0.3. For 97 out of the 199 categories, the correlation is significantly negative at the 5% confidence level. The panel (b) shows the case for price decreases. Similar observations can be made as in the case of price increases. Namely, the median of the correlation is -0.17 and the peak lies around -0.2 to -0.3.

For 114 out of the 199 categories the correlation is significantly negative at the 5% confidence level.

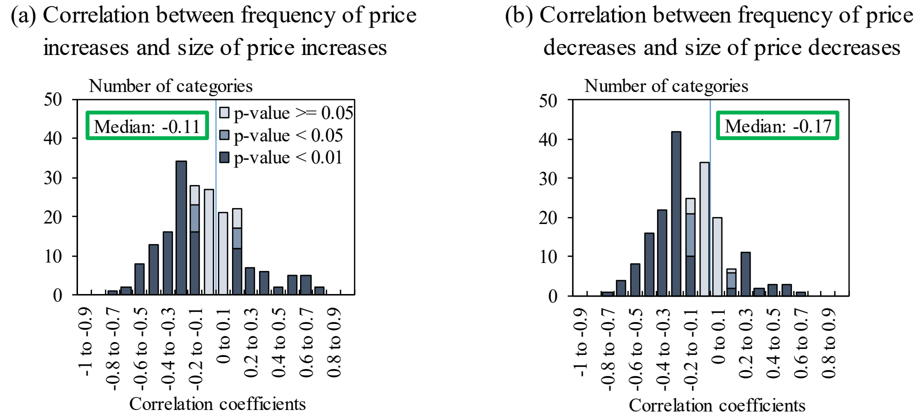


FIGURE 5. CORRELATION BETWEEN FREQUENCY AND SIZE OF PRICE CHANGES

Notes: The panels show the histogram of the correlations between the seasonal component of the frequency of price increases (decreases) and the size of price increases (decreases) for all 199 categories.

C. Seasonal Patterns of Inflation

The left panel of Figure 6 shows the seasonal components of the inflation, averaged over the entire sample year, for the category "tofu," and the right panel shows the corresponding seasonal components for all categories. The solid line in the right panel represents the median and the shaded area represents the 25th-75th percentile band across categories.

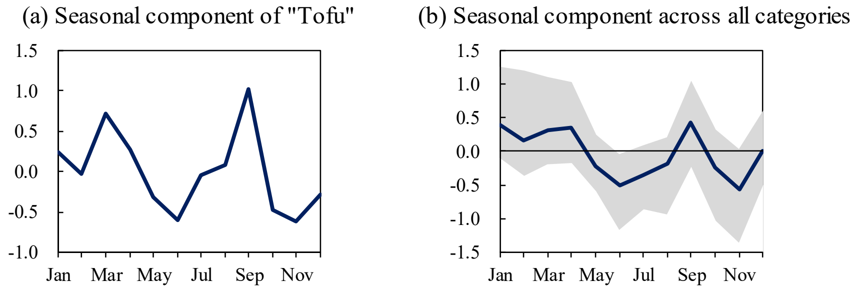


FIGURE 6. POS INFLATION RATE

Notes: The left panel plots the POS inflation rate of the category "soybean curd and its products, Tofu." The right panel shows the median of the average seasonal component of the POS inflation rate across all categories. The shaded area indicates the 25th and 75th percentile bands.

For the category "tofu," the inflation rate increases in March and September, as is seen in the frequency of price changes. For all categories, the seasonal pattern differs slightly from that of the frequency of price changes. It tends to be high in January, February, March, April, and September and low in other months.

To see the relationship between the frequency or size of price changes and the inflation rate, we construct two series which we refer to as net frequency and net size. For the former, we subtract the seasonal component of the frequency of price decreases from that of price increases. For the latter we subtract the seasonal component of the size of price decreases from that of price increases. Figure 7 shows the two series for all categories, with the median depicted in blue, together with the median of seasonal component of the POS inflation rate across categories. Similar to the seasonal component of the POS inflation rate, the net frequency tends to be high in January, February, March, April, and September and low in other months. This pattern arises from the asymmetry between the frequency of price increases and decreases. While both series tend to be high in March and September, a rise in the two months and a fall in the months from May to August are larger for price increases and a fall in January and February is larger for price decreases. The net size does not match well with the seasonal pattern of the POS inflation rate.

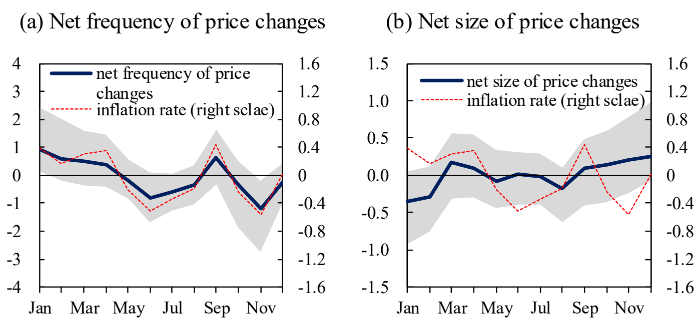


FIGURE 7. SEASONALITY OF NET FREQUENCY AND NET SIZE OF PRICE CHANGES

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.

Figure 8 studies the degree of synchronization in the POS inflation rate across categories, based on the correlation of the seasonal component of the POS inflation rate over the sample period for each of the 19,701 pairs. There is a modest degree of synchronization across pairs. The median is 0.10 and the peak lies around 0.0-0.1, and while 9,160 pairs, about 46% of the total number of pairs, are significantly positively correlated at the 5% confidence level.

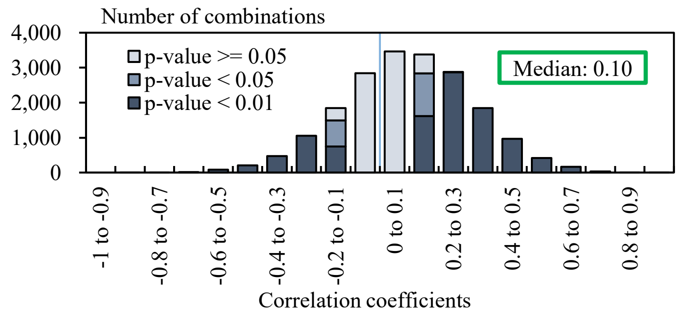


FIGURE 8. CORRELATION OF POS INFLATION RATE ACROSS CATEGORIES

Notes: The plot shows the histogram for the correlations of the seasonal component of the POS inflation rate across pairs of 199 categories.

D. Changes in Seasonal Patterns over Time

Lastly, we examine how the seasonal components of the frequency and size of price changes have changed over time. Figure 9 shows the yearly time-series of the POS inflation rate and the standard deviation of the seasonal components of the frequency of price increases and decreases for the category “tofu” and for all categories. For the standard deviation, we first estimate the coefficients in equation (4) and compute the standard deviation of the twelve coefficients for each year. The greater the variation across months is within the year, the higher the value is. For price increases, the standard deviation roughly tracks the time path of the POS inflation rate for both “tofu” and all categories. The standard deviation is large during the high inflation period in the first two years of the 1990s, falls to a low level in 1993, and remains at a low level until it starts to increase in the mid-2000s, as does the POS inflation rate. For price decreases, the standard deviation does not move together with the POS inflation rate. For example, it stays at a low level in the early 1990s when the POS inflation rate is high.

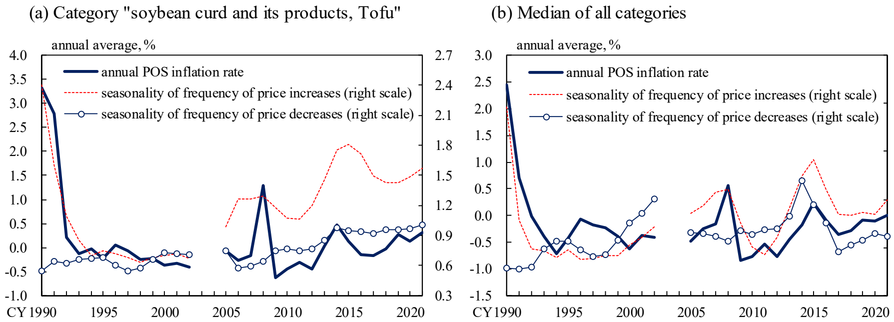


FIGURE 9. ANNUAL INFLATION AND SEASONALITY OF FREQUENCY OF PRICE CHANGES

Notes: Annual POS inflation rate is the annual average of the monthly inflation rate. The dotted line and the solid line with circle marker indicate the standard deviation of the seasonal component of the frequency of price increases and price decreases during the year, respectively. For all categories, the median of all 199 categories in each year is shown.

Figure 10 shows the case for the size of price changes. Roughly speaking, for "tofu," the standard deviation tracks the time path of the annual POS inflation rate. Compared with the frequency of price changes, not only the standard deviation of the size of price increases but also that of price decreases is high during the early 1990s. For all categories, the relationship is less clear.

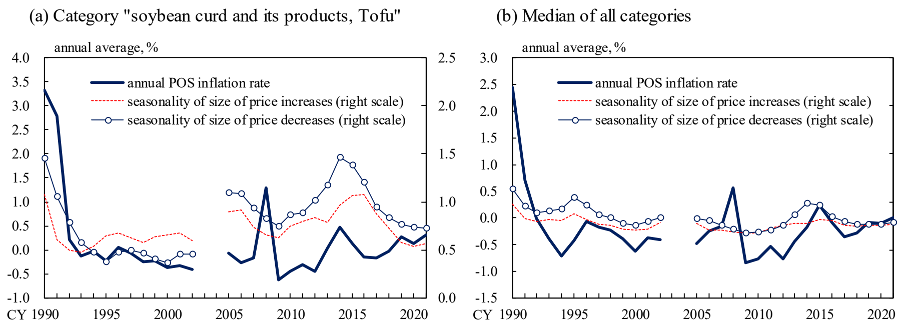


FIGURE 10. ANNUAL INFLATION AND SEASONALITY OF SIZE OF PRICE CHANGES

Notes: Annual POS inflation rate is the annual average of the monthly inflation rate. The dotted line and the solid line with circle marker indicate the standard deviation of the seasonal component of the size of price increases and price decreases during the year, respectively. For all categories, the median of all 199 categories in each year is shown.

Figure 11 looks at the relationship between the seasonal pattern of price changes and the inflation rate from a different angle. For each of the categories, we split the sample period into two sub-samples, a high inflation period and a low inflation period, depending on the yearly POS inflation rate and see how the seasonal patterns differ across the two subsample periods. Ups and downs across months are slightly more volatile for the frequency of price increases in the high inflation period compared with the low inflation period. Regarding the frequency of price decreases, ups and downs are more volatile in the low inflation period than the high inflation period. Such a difference is not seen for the size of price changes.

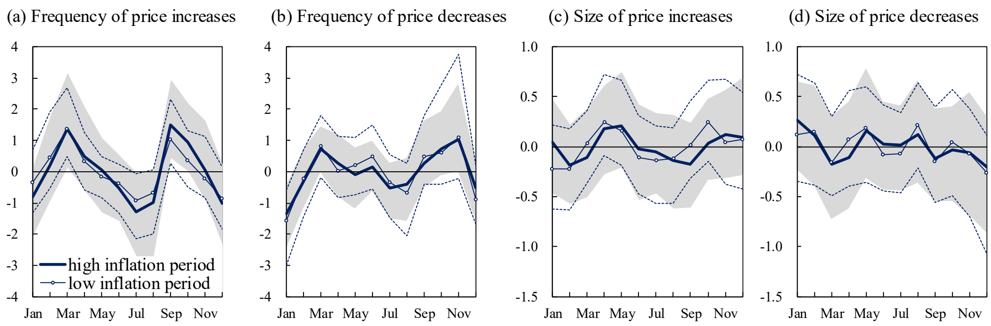


FIGURE 11. SEASONALITY IN HIGH AND LOW INFLATION PERIODS

Notes: The panels plot the average seasonal component in the high and the low inflation periods 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 a year in the top 10% of annual inflation during the whole sample period, and the low inflation period is defined as a year in the bottom 10% for each of the categories. The shaded area and dotted line indicate the 25 and 75 percentile bands.

Indeed, it can be shown formally that the seasonal patterns of the frequency of price changes are responsive to annual changes in the category-level inflation rate for the year. In Figure 12, the panels (a) and (b) show the distribution across categories of the correlations between the standard deviation of seasonal component of the frequency of price changes and its annual POS inflation rate. For price increases, the median is 0.38 and the peak lies around 0.4 to 0.5. Furthermore, for 97 out of 199 categories, the correlation is significantly positive at the 5% confidence level. For price decreases, the median is -0.12 and the peak lies around

0.0 to 0.1. For 30 out of 199 categories, the correlation is significantly negative at the 5% confidence level. In other words, the seasonal component of the frequency of price increases (decreases) becomes more volatile (less volatile) when the category-level annual inflation rate for the year is high. The relationship with annual category-level inflation is less clear for the size of price changes. The panels (c) and (d) show the distribution across categories of the correlations between the standard deviation of seasonal component of size of price changes and that category's annual POS inflation rate for the year. For price increases, the median is 0.10 and the peak lies around 0.2 to 0.3. For 23 out of 199 categories, the correlation is significantly positive at the 5% confidence level. For price decreases, the median is also 0.10 and the peak lies around 0.2 to 0.3. For 24 out of 199 categories, the correlation is significantly positive at the 5% confidence level.[10]

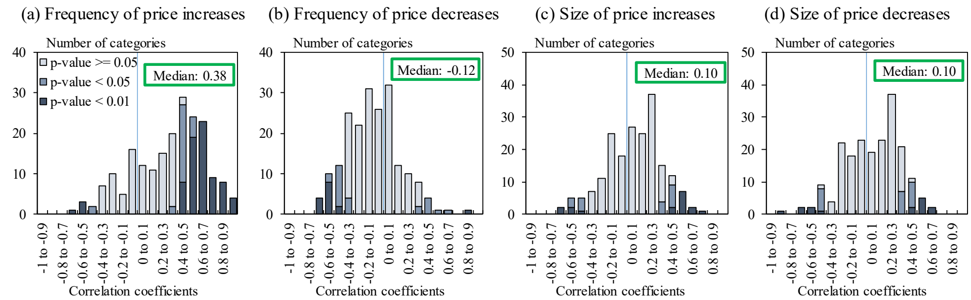


FIGURE 12. CORRELATION BETWEEN SEASONALITY OF PRICE CHANGES AND ANNUAL POS INFLATION

Notes: These panels show histograms of the correlations between the annual POS inflation rate and the standard deviation of the seasonal components for (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.

V. Simulation Using Menu Cost Models

What features of the economic structure are responsible for the observations obtained above? To see this, in this section we construct a simple menu cost model

[10] Though we show here that the seasonal cycle of the frequency of price changes varies with the annual inflation rate, the seasonal pattern itself has been stable in particular when compared with the seasonal cycle of the size of price changes. See Online Appendix E for the details.

and simulate the time path of the frequency and size of price changes as well as that of inflation under various assumptions on the source of seasonality.

Our model is built upon the partial equilibrium model used by Nakamura and Steinsson (2008) and is extended with seasonal variations to either of the two key model ingredients: the size of menu costs and the size of real marginal costs. This setting aims to address two views in the existing studies regarding what generates seasonality of price changes, a time-dependency element underscored in Nakamura and Steinsson (2008) and changes in the flexibility of wages during a specific quarter of the year underscored in Olivei and Tenreyro (2010). See also Online Appendix A for the details of our model.[11]

A. Outline of the Models

As in Nakamura and Steinsson (2008), we consider a monopolistically competitive market in which firms set their prices so as to maximize their profits subject to costs associated with price changes. Firms take changes in real wages, denoted as $\omega_{m(t)}$, and idiosyncratic technology, denoted as $A_t(z)$, as given and set their price, denoted as $p_t(z)$, so as to maximize the present value of the profits from now and beyond. Firms are allowed to set prices only if they pay the menu cost, denoted as $\omega_{m(t)}K_{m(t)}$. Note that the menu cost is driven by the real wage $\omega_{m(t)}$ and the menu cost specific component $K_{m(t)}$. Due to the menu cost, firms' current price $p_t(z)$ can deviate from the optimal price $p_t^*(z)$ that would prevail in a hypothetical economy where the menu cost is absent. Firms change their price

[11] Note that we do not explicitly consider models that extend purely time-dependent models, such as that of Taylor (1980) and Calvo (1983), by introducing exogenous seasonal variations in frequency of price changes. This is because the second and fourth findings, i.e., the (weak and) negative correlation between the frequency and size of price changes and the responsiveness of the frequency of price changes to changes in category-level inflation, do not accord well with the prediction of these pure time-dependent models. It is also notable that existing studies, such as Golosov and Lucas (2007) and Nakamura and Steinsson (2008), already argue that the standard Taylor and Calvo models do not agree with key facts observed in micro price data other than seasonality.

when the absolute value gap between the two prices $|p_t(z) - p_t^*(z)|$ is sufficiently large so that it is profitable for them to change the price even after paying the menu cost. The value of a firm is described by the equation below.

The state variables consist of the relative price $P_t^{-1} p_{t-1}(z)$ and the technology level $A_t(z)$. Clearly the gap $|p_t(z) - p_t^*(z)|$ changes with these variables.

$$(5) \qquad V_{m(t)}\left(\frac{p_{t-1}(z)}{P_t}, A_t(z)\right)$$

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

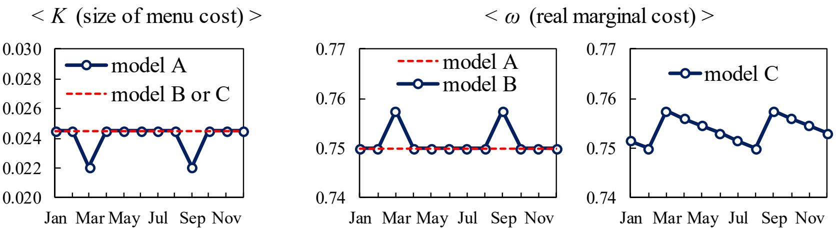
$$\left. + \beta \mathrm{E}_t V_{m(t+1)}\left(\frac{p_t(z)}{P_{t+1}}, A_{t+1}(z)\right)\right]$$

We consider three versions of the model, which we call models A, B, and C hereafter. The model settings as well as the differences between the three models are shown in Figure 13. The top panels show the settings regarding the menu cost component $K_{m(t)}$ and the real wage $\omega_{m(t)}$. As for the menu cost component $K_{m(t)}$, it declines in March and September in model A, whereas it stays constant throughout the year in models B and C. As for the real wage $\omega_{m(t)}$, it stays constant throughout the year in model A, whereas it increases in these two months in models B and C.[12] The latter two models differ in terms of the pace at which once increased

[12] For models B and C, we choose these settings only for the purpose of showing how seasonal cycles of real marginal costs affect seasonality of price changes. Admittedly, there are other ways to calibrate seasonal cycles of real marginal costs. One way is to use the actual seasonal patterns of real wages themselves instead of the series shown in the upper panels of Figure 13 that are generated in an ad hoc manner. Based on the data of the Monthly Labour Survey from 1990 to 2019, the seasonal component extracted by the X12 filter has two peaks, similar to model B, but in June and December for "Total Cash Earnings," reflecting the bonuses typically paid during the summer and winter. The seasonal component of the "Scheduled Cash Earnings" data, that is considered less affected by bonuses show no pattern of seasonal peaks except that it declines in January and slightly increases in April and June. Based on our simple state-dependent pricing model, both seasonal patterns of real wages induce a negative correlation between the frequency of upward price changes and the frequency of downward price changes and a positive correlation between the frequency and size of price changes, contrasting with the observations based on our scanner data.

real wages revert back to their original level. Note that we assume that firms are fully informed of these seasonal changes in menu costs or real marginal costs. The middle table (b) in Figure 13 shows other model parameters. The values are almost the same as those in Nakamura and Steinsson (2008). The qualitative results of our simulation presented in this Section are not sensitive to these model parameters. The bottom panels show the seasonal patterns of the implied nominal wage that are computed from the annual inflation rate, exogenously set to be 2%, and variations in the real wage in the three models. In model A, the nominal wage increases one-for-one with the inflation rate. In models B and C, the nominal wage exhibits seasonal variations.

(a) Parameters with seasonality



(b) Other parameters

	Parameters	Value
β	Subjective discount factor (monthly)	$0.96^{1/12}$
θ	Demand elasticity	4
C	Demand	1
ρ	Stickiness of idiosyncratic shocks	0.66
σ	Size of idiosyncratic shocks	0.0428

(c) Implied nominal wage

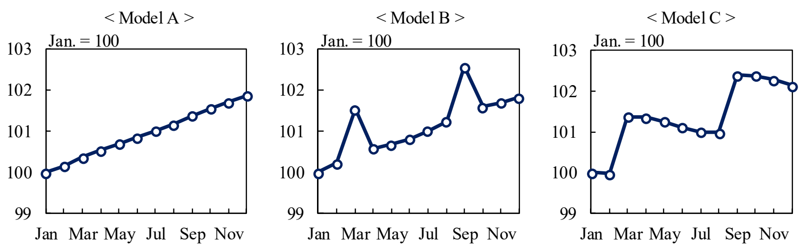


FIGURE 13. MODEL PARAMETERS

In our simulation, for each of the models, we focus on what we refer to as the cyclical steady state. In this steady state, while each firm faces uncertainty due to the presence of idiosyncratic shocks, there is no uncertainty at the aggregate level. Because of seasonal variations in parameters, i.e., $K_{m(t)}$ for model A and $\omega_{m(t)}$ for models B and C, there are monthly changes in the endogenous variables, such as the frequency and size of price changes. However, these variables return to the same value after a period of one cycle. Note that the sum of monthly inflation rates over 12 months equals the predetermined value of 2% unless noted otherwise.

B. Model-Generated Seasonal Patterns

Figure 14 shows the time path of (a) the frequency of price changes and (b) the size of price changes under the three models from January to December. In model A, the frequency increases in March and September for both price increases and decreases. Other things being equal, in this model, firms are incentivized to change prices in March and September even when the absolute value of the gap between the desired and actual price $|p_t(z) - p_t^*(z)|$ is not so large. Consequently, the average of the size of price changes made by firms changing prices in these months tends to be smaller than in the other months. For the twelve samples here, the correlation between the frequency of price increases and decreases is 0.96, that is, positive, which is qualitatively consistent with the observation (i) in Section IV. The correlation between the frequency and the size of price increases is -0.92, and that of price decreases is -0.86, both of which are negative as in the observation (ii) in Section IV. Admittedly, there are quantitative differences from the actual data, but model A at least agrees with the data qualitatively in terms of the sign of the correlation of these variables.

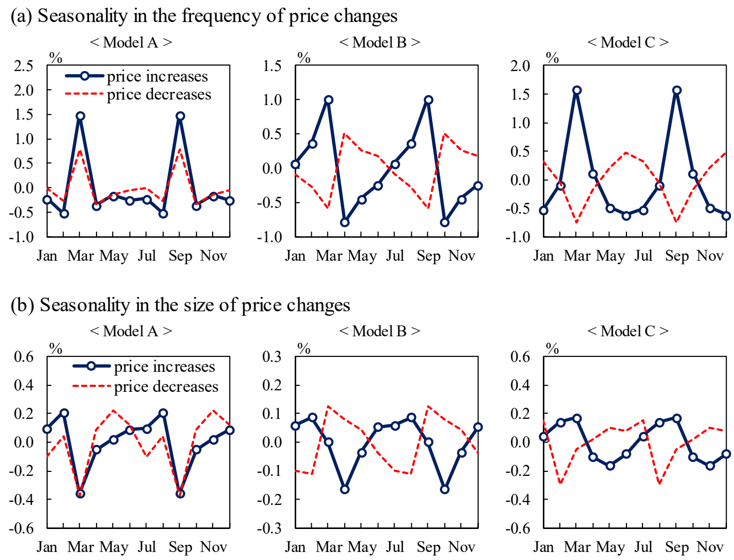


FIGURE 14. SEASONALITY OF PRICE CHANGES IN THE MODELS

Notes: Each panel indicates the seasonality in the frequency and the size of price increases and decreases in each model under 2% annual inflation. The seasonality is obtained by subtracting the annual average from the corresponding series.

The frequency of price increases rises in March and September as well in models B and C. In these models, the desired price for firms $p_t^*(z)$ rises in March and September due to the rise in real marginal costs. Therefore, for firms whose current price is lower than the desired price, the price gap $p_t^*(z) - p_t(z)$ becomes larger, which motivates these firms to pay the menu costs and set a higher price. In contrast to model A, however, the frequency of price decreases falls in March and September. This is because a rise in the real marginal cost reduces the price gap $p_t(z) - p_t^*(z)$ for firms whose current price is higher than the desired price, which in turn disincentivizes these firms from reducing their prices.

The dynamics of the size of price changes in models B and C is more complicated. On the one hand, if the problem were static and firms independently maximized their current profits, the rise in the desired price in March and September would contribute to larger price increases and to smaller price decreases in these months than in other months. On the other hand, the dynamic and collective nature of equation (5) introduces additional mechanisms. For example, higher frequency of price increases in March and September leaves a smaller number of firms whose prices are not adjusted to the desired prices, shrinking the range of the distribution of firms' prices. This mechanism contributes to the reduction of the average size of price increases in the following months (April and October). The mixture of these different mechanisms lead to complicated behavior in the evolution of the size of price changes.

The key differences between model A and the other two models are two-fold. First, whereas in model A the frequency of price increases and that of price decreases are positively correlated, in the latter two models the correlation is negative. Second, whereas the frequency and size of price changes are negatively correlated in model A, the same does not hold in models B and C. The results in model B and C do not agree with the empirical observations even qualitatively. For model B, the correlation between the frequency of price increases and decreases is -0.99, which is negative, and the correlation between the frequency and the size of price changes is modestly positive, specifically 0.57 and 0.06 for price increases and decreases, respectively. For model C, the correlation between the frequency of price increases and decreases is -0.96, which is again negative, and the correlation between the frequency and the size of price changes is again modestly positive, specifically 0.61 and 0.44 for price increases and decreases, respectively.

Figure 15 shows the time path of inflation rates at the top and that of net frequency of price changes at the bottom under the three different models. In all of the models, the inflation rate increases in March and September and, as in the observation (iii) in Section IV, the time path of net frequency traces that of the inflation rate. This is because, as shown in Figure 14, the seasonal variations in the frequency of price changes are more volatile than those in the size of price changes in all three of the models.

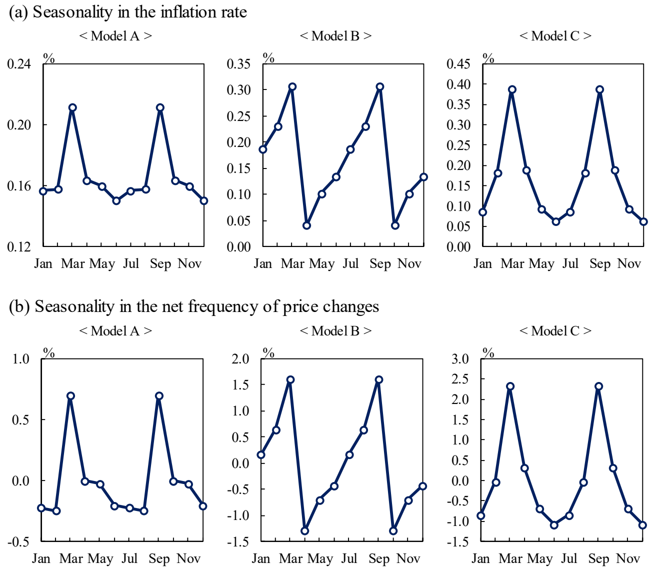


FIGURE 15. SEASONALITY OF INFLATION RATE IN THE MODELS

Notes: Each panel indicates the monthly inflation rate and the monthly net frequency in each model when the annual inflation rate is set to 2%. The seasonality is obtained by subtracting the annual average from the corresponding series.

Figure 16 shows the time path of the frequency and size of price changes under various settings of the annual inflation rate in model A. It can be seen that as the annual inflation rate increases, the seasonal patterns of the frequency of price increases become more volatile. In other words, the difference between the level of the frequency in the two months, March and September, and the other ten months becomes larger when the annual inflation rate is higher. In contrast, as the annual inflation rate increases, the seasonal patterns of the frequency of price decreases become less volatile. In other words, the difference between the two months and other ten months shrinks. This is because when the annual inflation rate is high, each month a larger portion of firms see a widening of the negative gap, $\mathrm{p_t(z)} - \mathrm{p_t^*}(z) < 0$, and these firms face an additional incentive to increase prices in particular during months in which the menu costs are low. By contrast, firms are less likely to face a positive gap, $\mathrm{p_t(z)} - \mathrm{p_t^*}(z) > 0$ under a higher annual inflation. This makes the small menu costs in March and September less effective in inducing firms to decrease their prices. The volatility of seasonality in the size of price changes, on the other hand, does not seem to depend on the annual inflation rate in a simple and monotonic way. All in all, the model-generated time path is qualitatively consistent with the data shown in Figure 12.

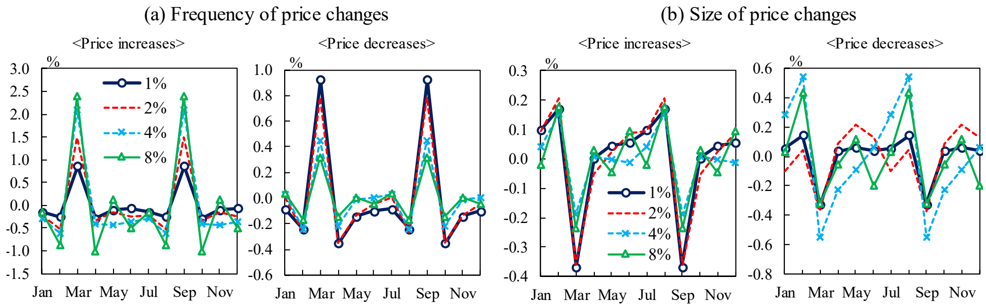


FIGURE 16. SEASONALITY AND INFLATION RATE IN THE MODEL A

Notes: Each panel indicates the seasonality in the frequency and the size of price increases and price decreases in model A for different annual inflation rates. The seasonality is obtained by subtracting the annual average from the corresponding series.

C. Discussion

Our simulation exercise underscores the importance of seasonal variations in menu costs in bringing the state-dependent model closer to the data. In the model, because the menu cost declines in a particular month, increases in the frequency of price increases and decreases become synchronized and the frequency and size of price changes become negatively correlated. In contrast, seasonal changes in real marginal costs alone are unable to reproduce these seasonal patterns observed in the data. In this sense, our results accord with the argument made by Nakamura and Steinsson (2008) stressing the importance of time-dependent elements in price dynamics.[13,14] Admittedly, however, while the model with seasonal cycles in menu costs does account for the key moments qualitatively, there is still a gap to be filled between the model and the data quantitatively. In particular, the model predicts a strong negative correlation between the frequency and size of price changes, contrasting with a weak correlation seen in the data.[15] Our simulation results should therefore be interpreted as stressing the role played by seasonal cycles in menu costs but should not be interpreted as indicating that other factors, including variations in real marginal costs, do not play a role.

The time-varying menu costs are to some extent consistent with the explanations of why prices are sticky as presented in early works, including Zbaracki et al. (2004) and Blinder et al. (1998). Using data from a large U.S. industrial manufacturer and its customers, Zbaracki et al. (2004) study the nature of menu costs and argue that managerial costs that consist of information gathering, decision making and communication costs, and customer costs that consist of communication and negotiation costs are quantitatively larger than the physical menu cost. These arguments imply that the size of menu costs can decline if communication and negotiation are smooth even when the physical menu costs do not change. Blinder et al. (1998), based on a survey of firms in the U.S., states that "firms might like to raise or lower prices, but hesitate to do so unless and until other firms move first. Once other firms move, they follow quickly." Put differently,

[13] It is also important to note that our model is not a pure time-dependent model such as that of Taylor (1980) or Calvo (1983), but instead consists of both time-dependent elements and state-dependent elements in one model. Indeed, the observation (iv), i.e., the responsiveness of the seasonality of the frequency of price changes to changes in the category-level inflation rate for the year, suggests the presence of a state-dependent element in the seasonal component of price changes in the data.

[14] Our argument that there are seasonal cycles in menu costs is related to the discussion of the CalvoPlus model analyzed in Nakamura and Steinsson (2010). They construct a menu cost model in which a certain fixed portion of firms receives an opportunity to change their prices at a low menu cost and the presence of these low-repricing opportunities that are largely orthogonal to the firms' desire to change the price mutes the selection effect.

[15] While it is true that the frequency and size of price changes are negatively correlated for a certain set of categories regardless of how one computes the seasonal components, the degree of the negative correlation differs depending on the methodology used for extracting the seasonal component. The negative correlation becomes salient when the seasonal component is computed by normalizing the original data with the annual data, as shown in Figure G1.

firms are less reluctant to raise or lower prices today if they know that other firms will move today. If there is a common expectation among firms that other firms will change their prices in March and September, for example, non-physical menu costs may fall, leading to an increase in the frequency of price changes.

These characteristics of menu costs have several broad implications for the understanding of price dynamics. While the standard model does not pay attention to changes in menu costs, assuming they are constant over time, if changes in menu costs play an important role in shaping the seasonality of price dynamics, the same mechanism may also be at play in price dynamics beyond the seasonal variations.[16,17] In other words, the inflation dynamics can vary in response to a change in menu costs even without changes in marginal costs or other economic conditions. In addition, with the size of menu costs differing across months, other things being equal, it is optimal for firms to reflect a change in the economic environment, including monetary policy shocks, in their prices in months in which menu costs are low. Consequently, the transmission of shocks to prices and then output may be altered depending on the month in which these shocks occur. This prediction accords well with the argument made by Olivei and Tenreyro (2010) that the month matters to the transmission of monetary policy shocks.

VI. Conclusion

Seasonality of price dynamics has been identified in a good number of existing studies, but a comprehensive picture, including a working mechanism behind the seasonality, has yet to be fully drawn so far. To fill the gap, we first study point-of-

[16] Admittedly, there are works that endogenize the degree of price flexibility in a New Keynesian framework, for example, Romer (1990) and Kimura and Kurozumi (2010). Changes in the degree of flexibility of prices in our model are, however, different from theirs in the sense that they depend on time rather than state.

[17] Indeed, Sudo et al. (2014), studying scanner data, as in this paper, from 1988 to 2013, document that the size of price changes has been declining and the frequency of price changes has been increasing over the sample period and argue that these secular changes may reflect a long-term decline in menu costs.

sale (POS) scanner data covering the period from 1990 to 2021 in Japan to draw an overall picture of seasonality of goods prices. Our empirical findings are as follows. First, the frequency of price increases and decreases tend to be high in March and September and low in other months for most categories. Second, for the majority of categories, seasonal cycles of the frequency of price changes are negatively correlated with those of the size of price changes. Third, the seasonal patterns of overall inflation track the seasonal pattern of net frequency, i.e., the difference between the frequency of price increases and that of price decreases, and are moderately synchronized across categories. Fourth, the pattern of seasonal cycles of the frequency of price changes is responsive to changes in the annual inflation rate of the category for the year. That is, the seasonality of the frequency of price increases (decreases) becomes more pronounced (less pronounced) when the category-level annual inflation rate is high.

Next, we conduct simulation exercises using menu cost models and explore the causes of seasonality of price changes. Our exercise shows the importance of seasonality in menu costs in generating seasonality of price changes in the data. Theoretically, when menu costs fall in March and September, firms are incentivized to change their prices in both upward and downward directions in the two months because it is less costly for firms to adjust prices in these months. This yields a positive correlation between frequency of price increases and that of price decreases and a negative correlation between the frequency and size of price changes.

The key contributions of the paper lies in documenting seasonal patterns of price dynamics in detail and offering an explanation for these patterns. While existing studies document the presence of seasonal patterns, they do not necessarily focus on the seasonality, nor study the causes and implications of the seasonality. This paper has some implications beyond the seasonality of price changes as well. First, synchronized ups and downs in the frequency of price changes underscore the importance of coordination rather than physical menu costs in explaining staggered price setting of firms. Second, the presence of seasonal cycles in menu costs indicates that the speed of transmission may change depending on the month in which the exogenous shock occurs, similar to the argument made by Olivei and Tenreyro (2010). If months matter in this sense, then central banks may also need to take into account the role of months in monetary policy implementation.

There are two caveats regarding this study. First, the current analysis only indicates that the observed seasonal patterns of price dynamics are consistent with the presence of seasonality in menu costs and that synchronization across categories of seasonality in menu costs can be interpreted consistently with the non-physical component of "menu costs" discussed in Zbaracki et al. (2004) or changes in implicit coordination among firms discussed in Blinder et al. (1998). The current paper is, however, silent about what have shaped seasonal patterns in menu costs (i.e., a fall in March and September and a rise in other months). The timing of seasonal cycles in menu costs may be related to the fact that the fiscal year begins in April and that changes in institutional settings, including various tax rates, are often made in April.[18] It may also be related to *Shunto*, as stressed in Olivei and Tenreyro (2010), though our simulation exercises suggest that changes in real marginal costs are not the dominant factor in shaping the seasonal patterns of price dynamics. Second, the nature of seasonal patterns of price dynamics may be different if service prices or prices in other jurisdictions are examined. Regarding the distinction between goods and services, for example, the official CPI tends rise in April and October for service prices, contrasting with goods prices that tend to rise in March and September as shown in Figure 1, which may indicate that the seasonal patterns of menu costs in service prices are different from those in goods

[18] See Bunn and Ellis (2012) for a related discussion for U.K. consumer prices. They document that a larger portion of prices increases in April than in other months and argue that "Excluding all sale prices, consumer prices are most likely to change in April. That could reflect changes in duties and/or firms changing prices to coincide with the start of a new fiscal year."

prices in Japan.[19] Exploring the deeper sources of the seasonal patterns and comparing the seasonal patterns of price changes across sectors and across countries may help improve our understanding of price dynamics, including the causes of price stickiness. These are left as the agenda for future research.

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[19] In Online Appendix H, we divide the sampled 199 categories into two groups "processed food" and "others," and study how the correlation within each of the groups differs from that across the two groups. Though the correlation tends to be lower across the groups, the key results are obtained qualitatively for the correlation across the groups.

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