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宗像晃、篠原武史、白塚重典、須藤直、渡辺努

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Institute for Economic Studies, Keio University
2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan
ies-office@adst.keio.ac.jp
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【要旨】

季節性は物価変動の最も顕著な特徴の一つであるが、数量の季節性や物価変動の景気循環的要素に比べると、その分析は著しく少ない。このギャップを埋めるため、日本の199カテゴリーの商品のスキャナーデータを使用し、1990年から2021年までの価格変動の季節性を実証的に研究する。分析結果からは、以下の４つの特徴がほとんどの品目分類で確認できる。(1)物価上昇・下落の頻度は3月と9月に上昇する、(2)物価変動の頻度に関する季節成分は物価変動の大きさの季節成分と負の相関がある、(3)インフレ率の季節成分はネットでみた物価変動の頻度の季節成分と一致する、(4)物価変動の頻度の季節パターンは物価変動の大きさの季節パターンに比べて安定している。しかし、このパターンは、その年の品目分類レベルの年間インフレ率の変化に反応する。次に、簡便な状態依存価格モデルを用いてシミュレーション分析を行い、メニューコストの季節的サイクルが、データで観察される価格変動の季節性を生み出す上で本質的な役割を果たしていることを示す。最後に、メニューコストの季節的サイクルの特性とマクロ経済変動への影響について議論する。

宗像晃
日本銀行金融機構局
kou.munakata@boj.or.jp

篠原武史
日本銀行金融研究所
takeshi.shinohara@boj.or.jp

白塚重典
慶應義塾大学経済学部
shigenori.shiratsuka@keio.jp

須藤直
日本銀行金融研究所
nao.sudou@boj.or.jp

渡辺努
東京大学大学院経済学研究科
watanabe@e.u-tokyo.ac.jp

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1 Introduction

It is widely known among both scholars and policymakers that the time series of prices have a sizable degree of seasonality, similar to quantity series. The top and middle panels of Figure 1 show the month-to-month change in the consumer price index (CPI) in Japan for all items and for goods less fresh food and energy, respectively, for selected years during the 1990s and 2000s. Generally speaking, prices tend to rise from the previous month around March and September and decline around June, though the pattern is less visible in the data for all items. The bottom panels of the same figure show the month-to-month change in the CPI in the U.S. for commodities less food and energy commodities. Indeed, the seasonal patterns are similar in the two countries. Figure 2 shows the decomposition of the yearly growth rate of the CPI, again 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.

Not surprisingly, such 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), pointing 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, states "seasonality of the frequency of price change" as one of the five noteworthy facts regarding price dynamics in the U.S. In the case of Europe, Álvarez et al. (2006), using granular data on consumer prices and producer prices, document that price changes tend to occur in the first quarter, in particular in January, and in September. 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

[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).

are not fully analyzed or not well understood 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 first decompose the inflation rate into frequency and size for upward price changes and downward price changes following Klenow and Kryvtsov (2008). We then extract the seasonal components of these series following Geremew and Gourio (2018) and study their characteristics including their interrelationships across categories and their relationship with the annual inflation rate. In extracting seasonal components, we use a regression with monthly dummy variables in our baseline. In addition to the baseline, as a robustness check, we also extract the seasonal components by two other methodologies, X12-ARIMA and dividing the original series by the annual average of the series, and redo the exercises.

For the theoretical analysis, we build a simple menu cost model 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 on top of the seasonal changes in wage flexibility. We address these two views in our exercise. We simulate two models, one with seasonal changes in real wages and the other with seasonal changes in menu costs and compare which of the two 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 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, though seasonal components of the size are less pronounced and less synchronized across categories and across the direction of price change relative to seasonal components of the frequency. Third, there is also seasonality in the inflation rate. 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 has been stable over the sample period, in contrast to that of the size of price changes. The pattern is, however, 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) in the sense that the standard deviation of monthly changes in the frequency becomes larger (smaller) 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.

Regarding our theoretical analysis, we find, based on our simulation exercises, 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. In contrast, a model with seasonal increases in real marginal costs does not generate the first two features, which starkly contrasts with the data.

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 should be 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 themselves. 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). Using data from a large U.S. industrial manufacturer and its customers, Zbaracki et al. (2004) study the nature of menu costs and document 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

[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. (2022), using original data and seasonally adjusted data. Blanco et al. (2022), 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.

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 2 overviews the literature. Section 3 explains the scanner data. Section 4 provides stylized facts on the seasonality of price changes. Section 5 develops a menu cost model that provides explanations for the seasonality of the changes. Section 6 concludes.

2 Literature Review

Broadly speaking, our study is related to three strands of literature. The first strand of studies includes works that specifically focus on seasonality of macroeconomic variables. Almost all of these works focus on quantity variables. They document characteristics of seasonality and explore the interaction between seasonal components and the business cycle component of a variable or derive macroeconomic implications of seasonality. 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. They also show that variations in the seasonal component of prices are small compared with those of quantity variables. From a slightly different angle, Beaulieu et al. (1992) show there is a strong positive correlation between the standard deviation of seasonal component and that of non-seasonal component of variables across countries and industries. Cecchetti and Kashyap (1996) and Matas-Mir and Osborn (2004) study interactions between seasonal cycles and business cycles using the data of advanced countries and show that summer shut-downs are shorter during boom years, which they interpret as the result of reallocation of production inputs from high output months to low output months.[3] Olivei and Tenreyro (2010) compare the

[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

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 in the frequency of price increases 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 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

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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.

and Nishioka (2007), Mizuno et al. (2010), Abe and Tonogi (2010), Watanabe and Watanabe (2014), Sudo et al. (2018), and Ueda et al. (2019) among others. 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 in the introduction, seasonality itself is already documented in some of these studies. For example, Nakamura and Steinsson (2008) and Álvarez et al. (2006) document that the frequency of price changes increases in January for both the U.S. and the euro area, respectively, and Bunn and Ellis (2012) document a rise in non-sale prices in April for the U.K. In contrast to our study, however, the seasonality is not the central focus of their study. Consequently, they do not formally extract the seasonal component of price changes nor study causes of seasonality using a theoretical model.

3 Data and Definition of Variables

3.1 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. 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 1 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.

3.2 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 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. Due to this definition of the regular price, we exclude the first and last 45 days of the sample for each product.

3.3 Definition of Variables

For the purpose of analyzing price dynamics in detail, following existing studies, such as Klenow and Kryvtsov (2008), we look at the intensive and extensive margins of price changes. To this end, 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 separate upward and downward changes, again following Klenow and Kryvtsov (2008). 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.

$$\pi_{Jt} = FREQ_{Jt}^{+}SIZE_{Jt}^{+} - FREQ_{Jt}^{-}SIZE_{Jt}^{-} \tag{1}$$

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.

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

Note that 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, following Sudo et al. (2014).[4]

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

[4] 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 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.

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.

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

Figure 3 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.[5] 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.

3.4 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 following equation for each of these variables, following Geremew and Gourio (2018).

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

[5] 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 below, 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 considered as the exit of an old product and the entry of a new product since the barcode has changed.

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

where $dum_{m,t}$ is a dummy variable that takes a value of unity 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.[6] Because, as we argue in Section 4, the degree of seasonality is time-varying, we estimate the above equation using rolling regressions with a three-year window. The degree 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.

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 Appendix B, we show the results when we use X12 for extracting seasonal components from the original series to analyze seasonal patterns. In Appendix C, 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 that are described in the main text.

How important are seasonal components quantitatively relative to variations of the variable in other frequencies? To see this, in Figure 4 we show three measures, all of which are constructed from the estimation results of equation (4). The upper 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 middle 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 bottom panel shows the statistical

[6] 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.

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 $\mathrm{m} = 1, \dots 12$, 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.

4 Observations

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

[1] For most categories, the frequency of both price increases and decreases tends to rise in March and September, exhibiting a two-humped pattern, with the former more pronounced than the latter.

[2] 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, though the seasonal components of the size of price changes are less pronounced and less synchronized across categories and across the direction of price change than those of the frequency of price changes.

[3] 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 and is moderately synchronized across categories.

[4] The seasonal pattern of the frequency of price changes has been stable over our

sample period relative to that of the size of price changes. The pattern is, however, 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. Such responses are not seen for the seasonal component of the size of price changes.

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

4.1 Seasonality of the Frequency of Price Changes

Figure 5 shows the characteristics of the seasonal component of the frequency of price changes for the category "tofu" at the top and all categories at the bottom. The top left panel shows the time series of the frequency for upward and downward price changes over the sample period and the top right panel shows their monthly seasonal components averaged over time. The bottom panels show the seasonal components averaged over time for all categories. Specifically, the solid lines 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. That is, the frequency is high in March and September and low in other months. In other words, the seasonal patterns of the frequency of price changes are synchronized for both upward and downward price changes. Second, similar seasonal patterns are observed for all categories, which implies that the synchronization is present across categories. .

Figure 6 studies the degree of synchronization of the seasonal component of the frequency of price changes both across categories and across directions (i.e. upward or downward price changes). The top panels show the degree of synchronization across categories, represented by the distribution of pairwise correlation coefficients. In particular, we compute the correlation of the seasonal components of the frequency of price increases (left) and decreases (right) over the sample period for every pairwise combination of categories. Note that there are 19,701 pairs (199 times 198/2). It can be seen that the seasonal components of the frequency of price changes are positively correlated for most of the pairs for price increases and decreases. For price increases, the peak lies around 0.1-0.2 and the median is 0.19. Furthermore, 12,233 pairs, which is about 62% of the total number of pairs, are significantly positively correlated at the 5% level. For price decreases, the peak lies around 0.2-0.3 and the median is 0.21. Furthermore, 12,975 pairs, which is about 66% of the total number of pairs, are significantly positively correlated at the 5% level.

The bottom panels show the synchronization of price increases and decreases within a category. We compute the correlation of the two time series, i.e., the seasonal components of the frequency of upward price changes and downward price changes, for each of the 199 categories. The correlations are computed using Pearson's correlation shown at the left and Spearman's rank correlation shown at the right. The two measures agree that the frequency of upward and downward price changes of a given category are positively correlated. For Pearson's correlation, the median of the correlations is 0.33 and the peak lies around 0.3-0.4. Furthermore, a positive correlation is observed at a statistical level of 5% for 150 of the 199 categories. On the other hand, a negative correlation is observed at a statistical level of 5% for only 11 categories. For Spearman's rank correlation, the median of the correlation is 0.44 and the peak lies around 0.6-0.7.

4.2 Seasonality of the Size of Price Changes

Figure 7 shows the characteristics of the seasonal component of the size of price changes for the category "tofu" at the top and all categories at the bottom. The top left panel shows the time series of the size of upward and downward price changes over the sample period and the top right panel shows the monthly seasonal components of the size of price changes averaged over time for the same category. The bottom panels show the seasonal components of the size of upward and downward price changes averaged over time for all categories. Specifically, the solid lines represent the median and the shaded area represents the 25th-75th percentile bands across categories. While there are some seasonal variations for both price increases and decreases, it is less obvious that these seasonal variations are synchronized across categories and/or across directions than is the case with the frequency of price changes. 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 upward and downward price changes, exhibiting a negative correlation with the frequency of price changes. This observation, however, does not hold clearly for all categories shown at the bottom. Indeed, for all categories, differences in the size of price changes across months are less visible compared with the case of the frequency of price changes.

How are the seasonal components of the size of price changes related to those of the frequency of price changes? To see this, we compute the correlation between the seasonal components of the frequency and size of price changes for each of the categories. The top left panel in Figure 8 shows the distribution across categories of the correlation between the frequency and the size of price increases. For Pearson's correlation, the median of the distribution is -0.11 and the peak lies around -0.2 to -0.3. For 97 out of the 199 categories, the correlation is negative at the 5% level. For Spearman's rank correlation, the median of the correlation is -0.01 and the peak lies around -0.1-0.0. These observations indicate that the seasonal components of the frequency and size of price increases are negatively, though modestly, correlated. The bottom panels of the same figure show the case for price decreases. Similar observations can be made as in the case of price increases. Namely, for Pearson's correlation, the median of the distribution is -0.17 and the peak lies around -0.2 to -0.3. Furthermore, for 114 out of the 199 categories the correlation is negative at the 5% level. For Spearman's rank correlation, the median of the correlation is -0.14 and the peak lies around -0.1-0.0.

Similar to the case of the frequency of price changes, we study the degree of synchronization for the size of price changes. In Figure 9, the top panels 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 (left) and downward (right) price changes separately. It can be seen that seasonal components of the size of price changes are positively correlated in most of the pairs, but the proportion of pairs exhibiting a positive relationship is limited compared with the case of the frequency of price changes. For upward price changes, the median is 0.07 and the peak lies around 0.0-0.1. Furthermore, 7,634 pairs, representing about 39% of the total number of pairs, are positively correlated at the 5% level and 2,694 pairs, representing about 14% of the total number of pairs, are negatively correlated at the 5% level. For downward price changes, the median is 0.08

and the peak again lies around 0.0-0.1. Furthermore, 8,082 pairs, representing about 41% of the total number of pairs, are positively correlated at the 5% level and 2,729 pairs, representing about 14% of the total number of pairs, are negatively correlated at the 5% level.

The bottom panels of the figure capture the degree of the synchronization between upward and downward price changes within a category. Using Pearson's correlation, we see that the sizes of price increases and decreases are positively correlated at a statistical level of 5% for 96 out of the 199 goods. The median of the distribution is 0.10 and the peak lies around 0.0 to 0.1. Using Spearman's rank correlation, we find that the median of the correlation is 0.10 and the peak lies around 0.1-0.3. Again, these numbers are less positive than in the case of the frequency of price changes where, for example, the median of the two correlation measures are 0.33 and 0.44.

To summarize, while synchronization of the seasonal component of the size of price changes is generally positive both across categories and across the direction of price change, the correlation coefficients are less positive than in the case of the seasonal component of the frequency of price changes, indicating that the degree of synchronization is more moderate for the former than the latter. In addition, for the majority of categories and for both price increases and decreases, seasonal component of the frequency of price changes are negatively correlated with those of the size of price changes.

4.3 Seasonal Patterns of Inflation

Now we turn our attention to the seasonal component of the category-level monthly inflation rate. Figure 10 shows the seasonal component of the POS inflation rate for the category "tofu" at the top and all categories at the bottom. The top left panel shows the monthly inflation rate over the sample period for "tofu," and the top right panel shows the seasonal component of the inflation rate for "tofu" averaged over time. The bottom panel shows the seasonal component of the monthly inflation rate averaged over time for all categories. Specifically, the solid line represents the median and the shaded area represents the 25th-75th percentile band across categories. For the category "tofu," the inflation rate increases in March and September, as is seen in the frequency of price changes. For all categories, however, 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 how the frequency and size of price changes affect the seasonal pattern of the inflation rate, we construct two series which we refer to as net frequency and net size hereafter. For the former, we subtract the seasonal component of the frequency of price decreases from that of price increases and for the latter we subtract the seasonal component of the size of price decreases from that of price increases. Figure 11 shows the net frequency and the net size of price changes 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 that of price decreases. While both series tend to be high in March and September, a rise in the frequency of price changes in the two months and a fall in the frequency of price changes in the months from May to August are more pronounced for price increases and a fall in the frequency of price changes in January and February is more pronounced for price decreases. Consequently, the seasonal pattern of the POS inflation rate generally tracks that of the net frequency. In contrast, the net size of price changes tends to be low in January and February and high in the fourth quarter of the year. This seasonal pattern does not match well with the seasonal pattern of the POS inflation rate.

Figure 12 studies the degree of synchronization in the POS inflation rate across categories. Similar to the exercises conducted above, we compute the correlation of the seasonal component of the POS inflation rate over the sample period for each of the 19,701 pairs (199 times 198/2). There is synchronization across pairs, though only modestly. The median of the distribution is 0.10 and the peak lies around 0.0-0.1. Furthermore, while 9,160 pairs, representing about 46% of the total number of pairs, are positively correlated at the 5% level, 3,343 pairs, representing about 17% of the total number of pairs, are negatively correlated at the 5% level.

4.4 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.

Variations over Time

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 13 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 14 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.

Seasonal Patterns and Economic Conditions

Though the seasonal patterns of price changes are stable at least for the frequency of price changes, it does not mean that they are unresponsive to changes in the macroeconomic environment. Figure 15 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” at the top and for all categories at the bottom. 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. There is modest asymmetry between price increases and decreases. 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, mirroring the increase in the POS inflation rate. In contrast, 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 and during the few years before the global financial crisis when the POS inflation rate is high.

Figure 16 shows the yearly time-series of the POS inflation rate and the standard deviation of the seasonal components of the size of price changes of "tofu" and all categories for both upward and downward price changes. Roughly speaking, for “tofu,” the standard deviation tracks the time path of the annual POS inflation rate. It is notable that, 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 17 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. It can be seen from the figure that 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 across months are more volatile in the low inflation period than the high inflation period, in particular when looking at changes in the 25th to 75th percentiles. Such a difference is not seen for the size of price changes.

Indeed, it can be shown more 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 18, the top panels 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 of the distribution is 0.38 and the peak lies around 0.4 to 0.5. Furthermore, for 97 out of 199 categories, the correlation is positive at the 5% level. For price decreases, the median of the distribution is -0.12 and the peak lies around 0.0 to 0.1. For 30 out of 199 categories, the correlation is negative at the 5% 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 bottom panels 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 of the distribution is 0.10 and the peak lies around 0.2 to 0.3. For 23 out of 199 categories, the correlation is positive at the 5% level. For price decreases, the median of the distribution is also 0.10 and the peak lies around 0.2 to 0.3. For 24 out of 199 categories, the correlation is positive at the 5% level.

5 Simulation Using a Menu Cost Model

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 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. In particular, Nakamura and Steinsson (2008) underscore the importance of a time-dependency element in the observed seasonal patterns of price dynamics and

Olivei and Tenreyro (2010) underscore the importance of changes in the flexibility of wages during a specific quarter of the year as a source of seasonality for Japan's price dynamics. See also Appendix A for the details of our model.

In addition, 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. Admittedly, among the four key findings listed above, the first finding, i.e., an increase in frequency of both upward and downward price changes in a specific month of the year, is considered consistent with the prediction of such time-dependent models. However, 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.[7]

5.1 Seasonal Cycles in Marginal Cost and Menu Cost

As in the model of 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. We assume that 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 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.

[7] 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.

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

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

$$\left. + \ \beta \mathrm{E}_t V_{m(t+1)}\left(\frac{p_t(z)}{P_{t+1}},\ A_{t+1}(z)\right)\right] \quad (5)$$

Note that 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.

We consider three versions of the model, which we call models A, B, and C hereafter. These models are identical except for the setting regarding either the menu cost component $K_{m(t)}$ or the real wage $\omega_{m(t)}$. In model A, we assume that the menu cost temporarily declines twice a year, in March and September, due to a decline in $K_{m(t)}$, and stays at a constant value in other months, while $\omega_{m(t)}$ is constant. In models B and C, we assume that real wages temporarily increase in March and September, while $K_{m(t)}$ is constant. The two models differ in terms of the pace at which once-increased real wages revert back to their original level. Note that we assume that firms are informed of these seasonal changes in menu costs or real marginal costs.

The settings are shown in Figure 19. 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.[8] The middle table shows other model parameters. The values are

[8] 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 19 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

almost the same as those in Nakamura and Steinsson (2008). 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.

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.

5.2 Model-Generated Seasonal Patterns

Figure 20 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. The correlation between the frequency and the size of price changes is negative, specifically -0.92 and -0.86 for price increases and decreases, respectively. Admittedly, there are quantitative differences

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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.

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.

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 21 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 data, the time path of net frequency traces that of the inflation rate. This is because, as shown in Figure 20, 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, which is consistent with our scanner data shown in Figure 4 as well.

Figure 22 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 positive annual inflation. These firms also reduce their prices in these months but the share of such firms is limited. 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 18.[9]

[9] Figure 23 shows the results of a similar simulation based on model C. It can be seen that as the annual inflation rate rises from 1% to 8%, the volatility of the seasonal cycle of the frequency of upward price changes increases and that of downward price changes decreases, similar to the results of model A. The seasonal pattern of the frequency of price changes, however, differs between price increases and price decreases in the sense that the frequency declines in March and September for

5.3 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.[10, 11] 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.[12] 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

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price decreases, whereas it rises in March and September for prices increases.

[10] 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 [4], 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.

[11] 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.

[12] 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 C1.

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, 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.[13,14] 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

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[13] 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.

[14] 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.

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.

6 Conclusion

Seasonality of price dynamics has been identified in a good number of existing studies, but a comprehensive picture, including the difference between upward price changes and downward price changes or the mechanism behind the seasonality, has yet to be fully drawn so far.

To fill the gap, we first study point-of-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, though the latter is less pronounced and less synchronized across categories and between the direction of price change. 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 has been stable relative to that of the size of price changes. The pattern is, however, 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 inflation rate for the year is high. Such responsiveness is not observed for the size of price changes. These observations are generally made regardless of the method used to extract seasonal components. The same general pattern is observed whether one uses a rolling regression with monthly dummy variables (our baseline), X12-ARIMA (shown in Appendix B), or the original series divided by the average of the same year (shown in Appendix C).

Next, we conduct simulation exercises using a menu cost model and explore the causes of seasonality of price changes. Our exercise underscores the importance of seasonal changes in menu costs in generating seasonal patterns of price changes that are consistent with 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 seasonal patterns. While existing studies document the presence of seasonal patterns, they are not necessarily focused on the seasonality itself, nor do they study the causes and implications of the seasonality. In addition to these points, this paper contributes to a better understanding of price dynamics in a broader context. For example, synchronized ups and downs in the frequency of price changes indicate the importance of coordination rather than physical menu costs in explaining staggered price setting of firms. In addition, 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). Also, if months matter in this sense, then the central bank may also need to take into account the role of months in monetary policy implementation and communication.

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 seasonal cycles in menu costs and that such seasonal cycles in menu costs can be interpreted as representing the non-physical component of "menu costs" discussed in Zbaracki et al. (2004) and possibly representing changes in implicit coordination among firms, as discussed in Blinder et al. (1998). The current paper is therefore silent about what factors have shaped seasonal patterns in menu costs in the way suggested by the data (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 changes in institutional settings, including various tax rates, are often made in

April.[15] It may also be related to *Shunto*, as stressed in Olivei and Tenreyro (2010), though the changes in wages themselves do not seem to play the dominant role in shaping the seasonal patterns of price dynamics. Second, the nature of seasonal patterns of price dynamics may be different from those documented in this study if seasonal patterns of service prices or those of products in other jurisdictions are examined. Regarding the distinction between goods and services, the monthly increase in the official CPI tends to be high in April and October for service prices, contrasting with goods prices that tend to be high in March and September, as shown in Figure 1, which may in turn indicate that the seasonal patterns of menu costs in the service sector may be slightly different from those in the goods sector. Regarding the difference across borders, while there are some similarities in terms of the seasonal patterns of inflation in the U.S. and Japan, as shown in Figure 1, the seasonal pattern of the frequency of price changes documented in Nakamura and Steinsson (2008) differs from ours. 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.

[15] 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."

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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 while paying a menu cost or not. The firm's policy function is influenced by seasonal variation in parameters, but is assumed to return to its original form after one cycle, corresponding to 6 months, under the cyclical steady state equilibrium that we focus on in this paper. 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.

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

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

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 $m(t) = \mathrm{mod}(t-1,6)+1$ 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:

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

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, $K_3 > K_1 = K_2 = K_4 \cdots = K_6$, 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 19.

We use the following iterative algorithm to obtain the solution:

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

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

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

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

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

F) Repeat steps (C) to (E) until convergence.

B. Characteristics of Seasonal Components Extracted by the X12 Filter

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 the X12 filter tend to vary less from year to year.

Figure B1 shows the seasonal components of the frequency and size of price changes for all categories extracted by the X12 filter. Figure B2 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 B3 shows the seasonal component of the POS inflation rate, together with the net frequency and the net size of price changes. Figures B4 and B5 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 the frequency or the size of price changes and the annual inflation rate of the same year.

It can be seen that for the four key observations, three of them hold true for the series extracted by the X12 filter. 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 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). The reason for the difference lies in the fact that the seasonal components of a year are computed using a longer window in the X12 filter 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, the estimated seasonal components of these years are affected by the realizations in the following years when the negative correlation became smaller.

C. 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 B, we show that the key observations generally hold for seasonal components extracted by the X12 filter. In this Appendix C, 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, the method applied in this Appendix C allows for flexible changes in seasonal components from year to year, which in turn implies that it could regard any idiosyncratic shocks as seasonality, overestimating the variation of seasonality.

Figure C1 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 components of the frequency of price increases are positively correlated with those of price decreases and those of frequency and size are negatively correlated for both price increases and decreases, indicating that observations [1] and [2] hold for this methodology as well.

Figure C2 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), variation in seasonality becomes high (low), indicating that observation [4] holds.

Figure C3 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 observation [3] also holds true for the series extracted by normalizing with the annual value.[16]

[16] Because the yearly value $\bar{y}_{Jt}$ of the POS inflation rate and the net frequency could be negative,

D. 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 1. 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 foods" and "others" - and compute the correlation of categories within each of the groups and across the two groups.

Figure D1 shows the degree of synchronization (a) across all categories, (b) within "processed foods," (c) within "others," and (d) between "processed foods" 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 foods" 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 "others" and less so for the pairs within "processed foods" 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 indicates a possibility that the degree of synchronization may be to some extent affected by the similarity of goods. Figure D2 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.

Figures D3 and D4 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.

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we subtract it from variable y_{Jt} instead of dividing for these series.

E. Number of Statistically Significant Monthly Dummies

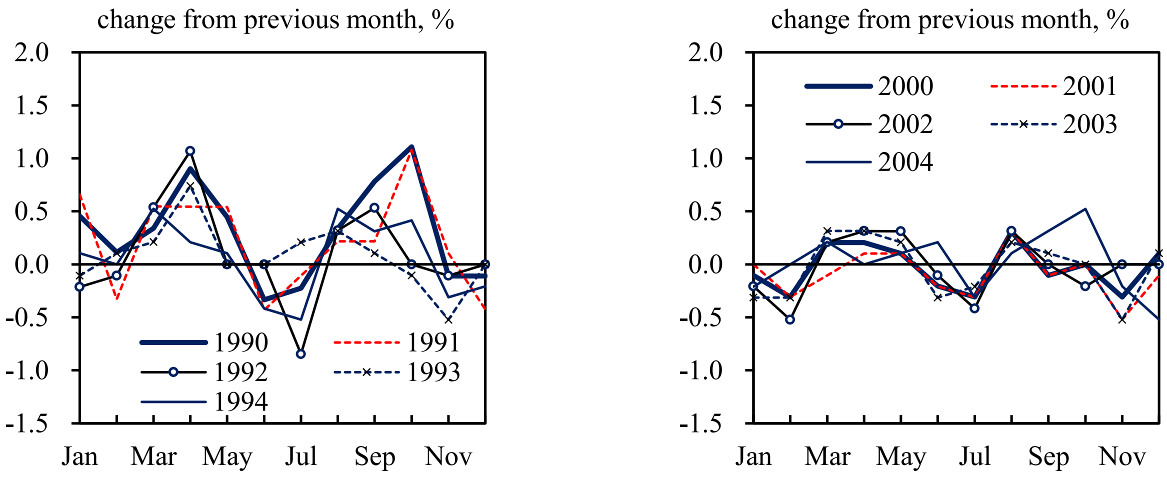
In the main text, we measure the size of seasonality with the size of the coefficients of monthly dummies in equation (4). Based on the measure, we show that the frequency of price changes has two peaks, rising in March and September and falling in June and that the size of price changes does not have 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 E1 shows 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 size of price changes, the number of dummies that are statistically significantly different from zero is far more moderate and the difference of the number of such dummies across months is less pronounced relative to the frequency of price changes.

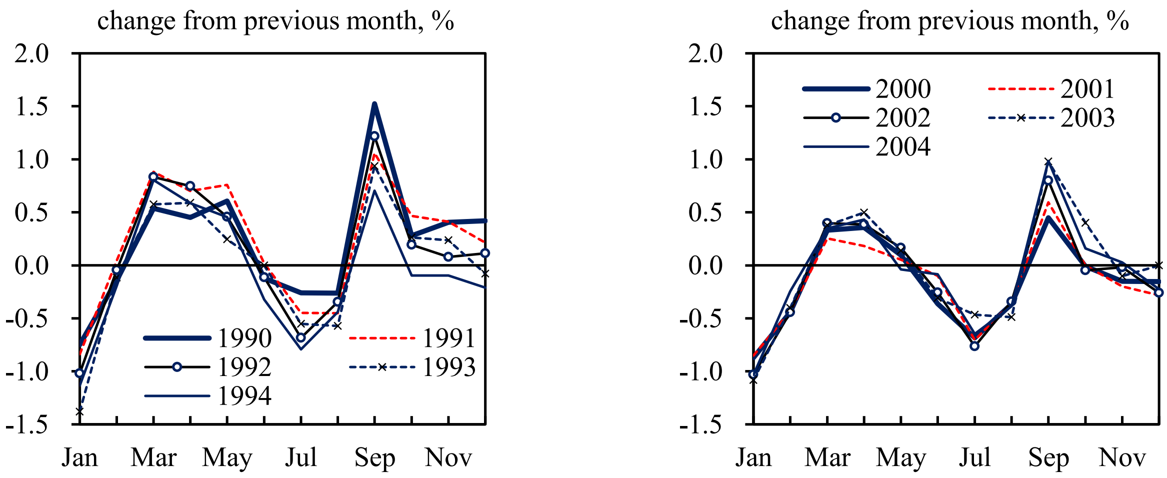
Figure E2 shows the case when the dummies are estimated based on the full-sample period instead of a three-year rolling estimation. Similar observations can be made to those shown in Figure E1.

Figure 1: Monthly Changes in CPI

(a) Japan (CPI, all)



(b) Japan (CPI, goods less fresh food and energy)



(c) US (CPI, commodities less food and energy)

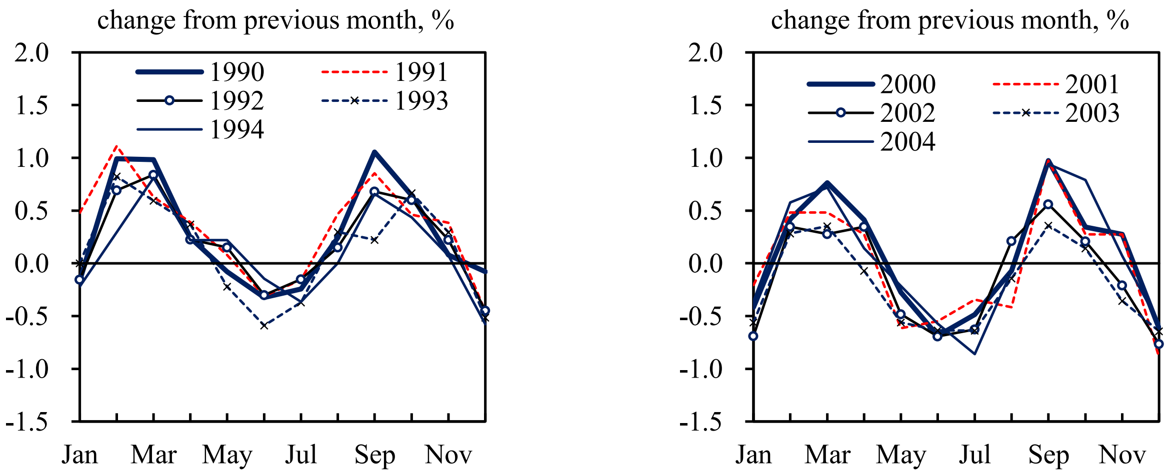
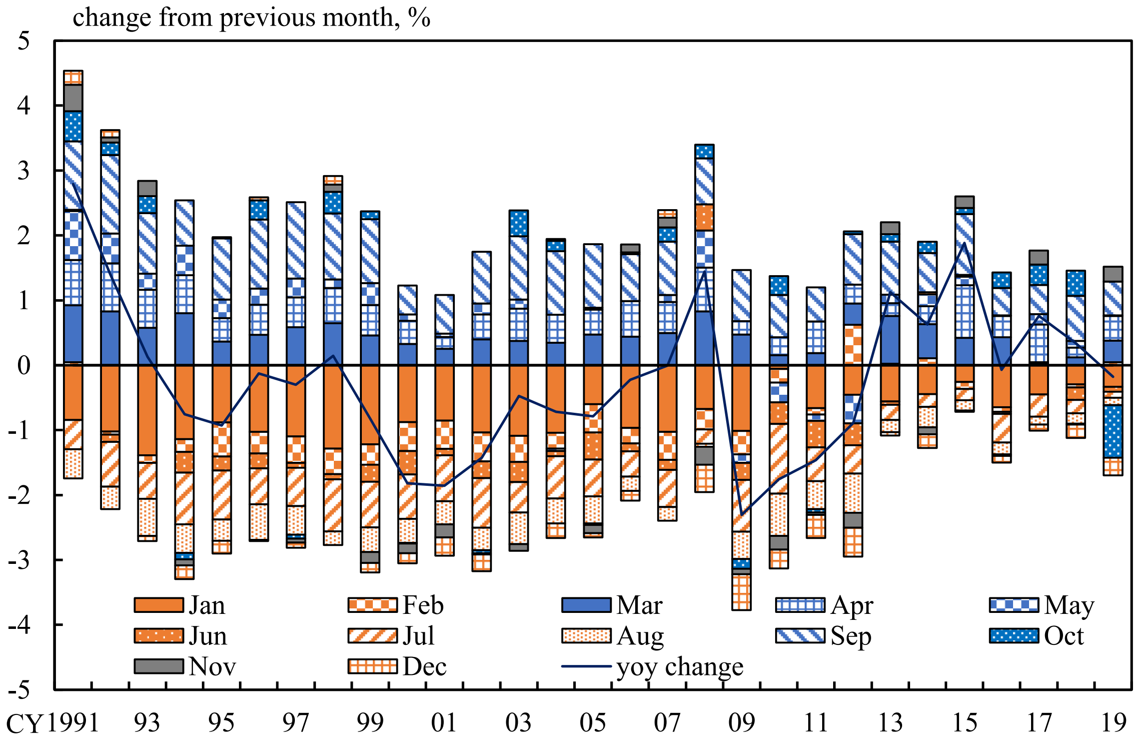
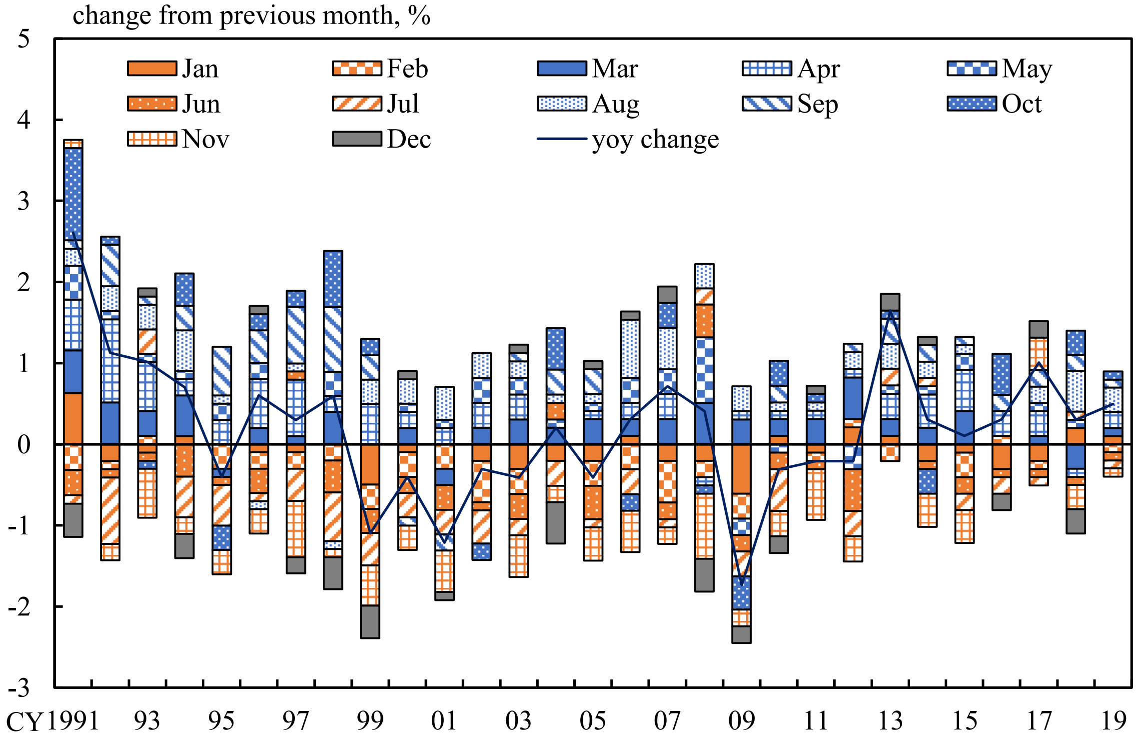


Figure 2: Decomposition of the Annual CPI Change in Japan

(a) CPI (goods less fresh food and energy)

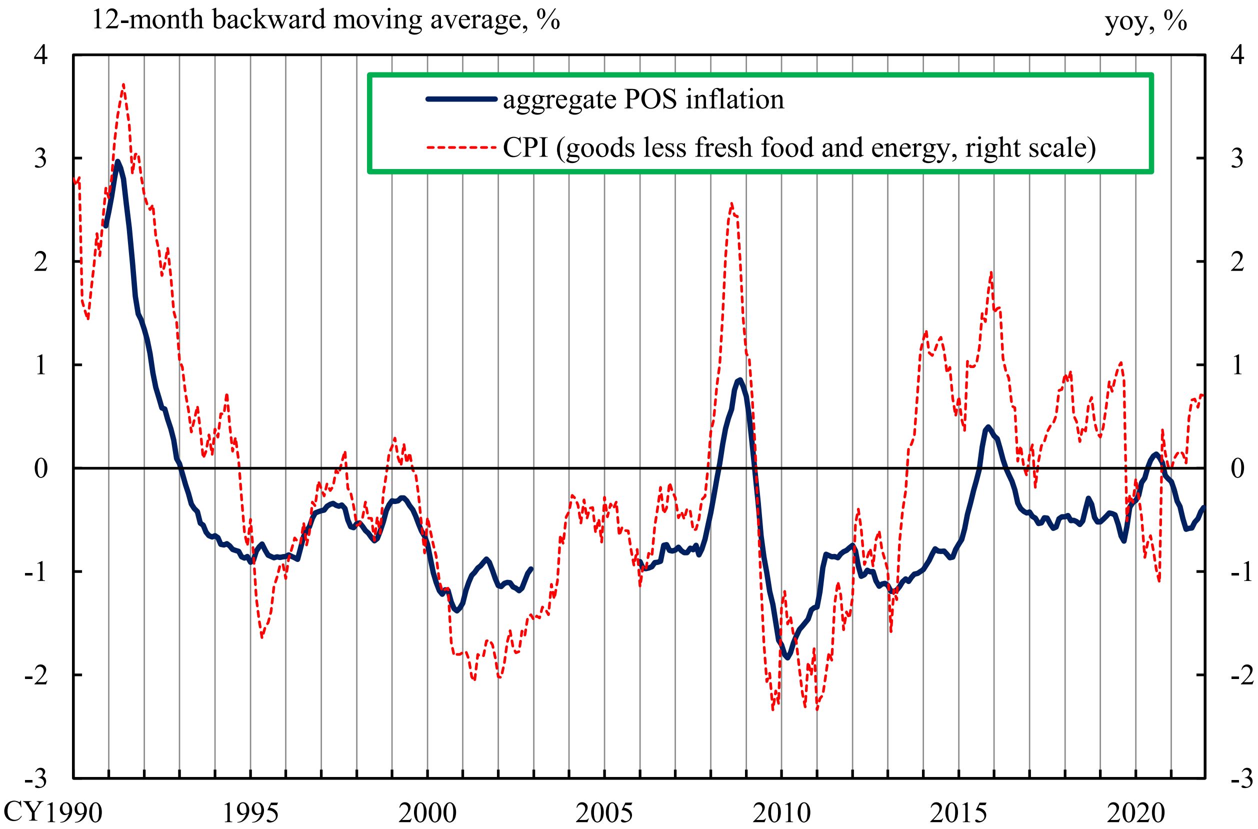


(b) CPI (all)



Note: The figures are adjusted for changes in the consumption tax rate.

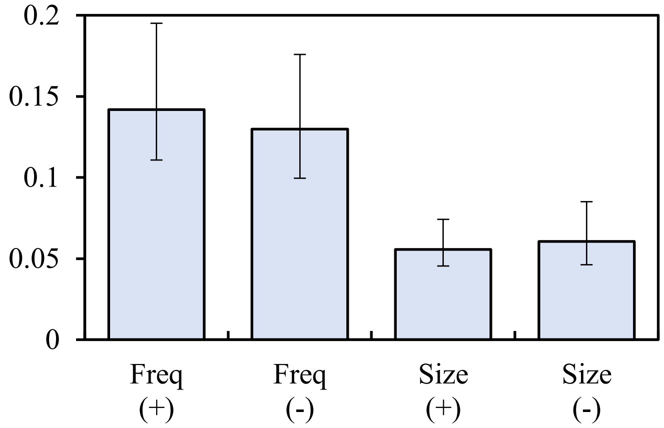
Figure 3: Aggregate POS Inflation



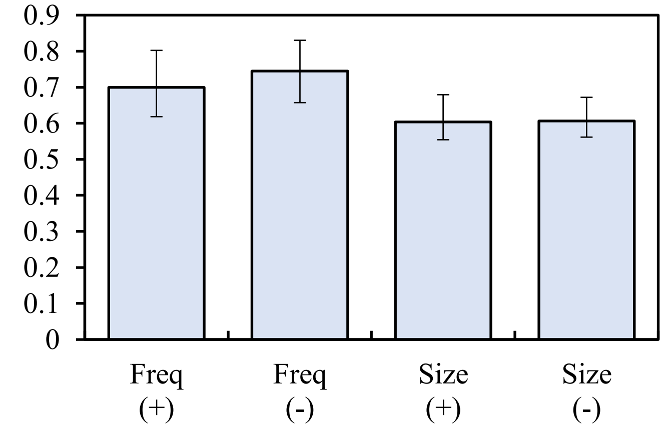
Notes: The CPI figures exclude the effects of the consumption tax hikes. Aggregate POS inflation is calculated as the weighted average of the inflation rate for each category weighted by sales.

Figure 4: Importance of Seasonality

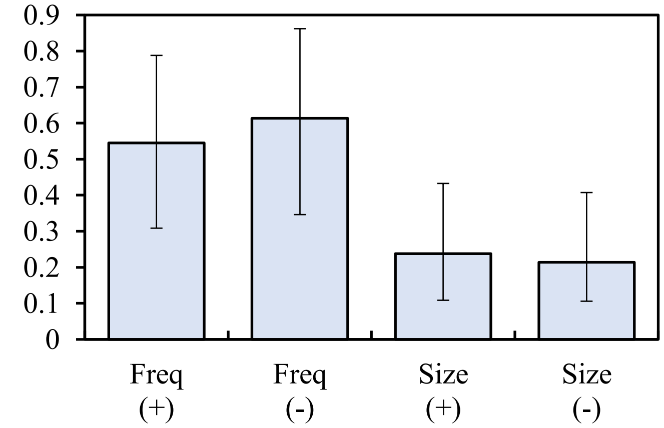
(a) Variations of seasonality relative to the original series



(b) Variations of seasonality relative to those of the detrended series



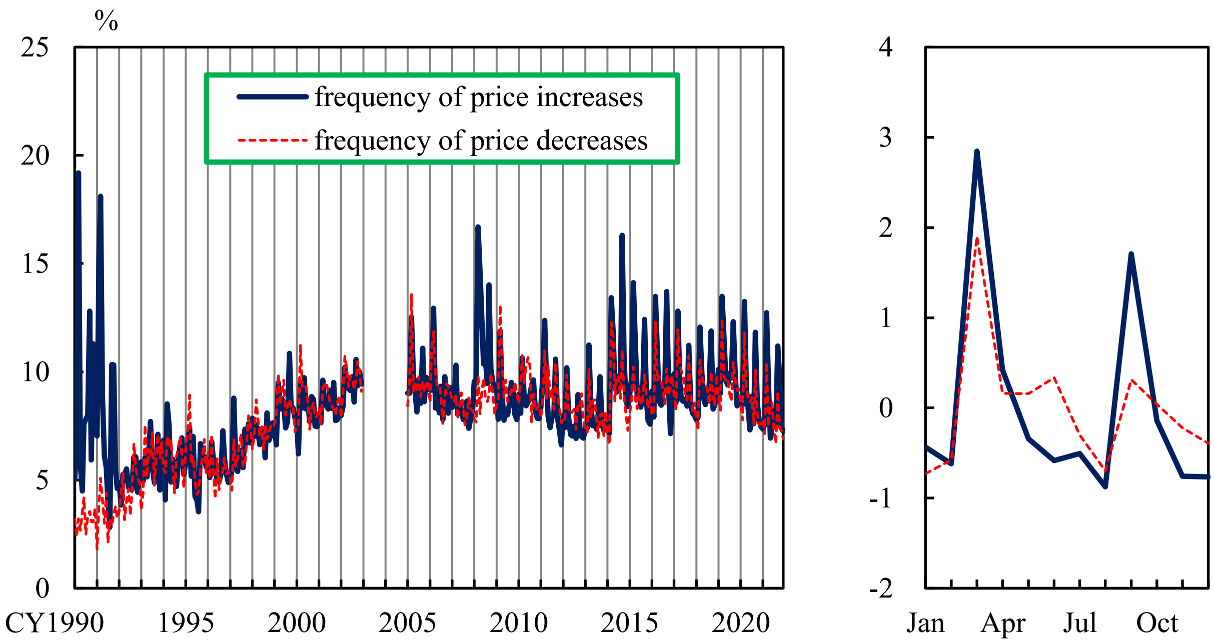
(c) Statistical significance of seasonality



Note: The upper and middle 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 bottom 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% level. All panels show the median of all categories and the error bands indicate the 25th and 75th percentiles.

Figure 5: Frequency of Price Changes

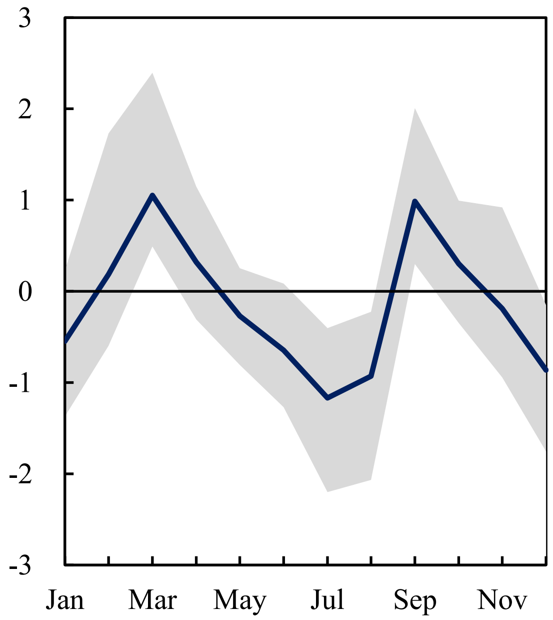
(a) Category "soybean curd and its products, Tofu"



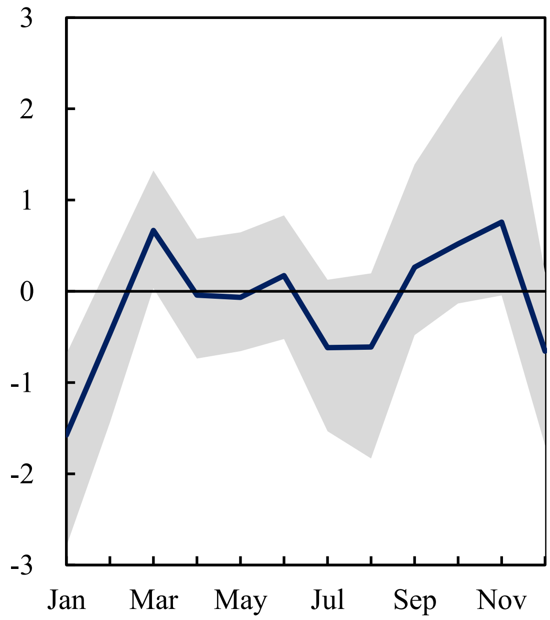
Notes: The left panel plots the frequency of price changes of the category "soybean curd and its products." The right panel shows the average seasonal component of the frequency of price increases and price decreases.

(b) Seasonal component across all categories

<Frequency of price increases>



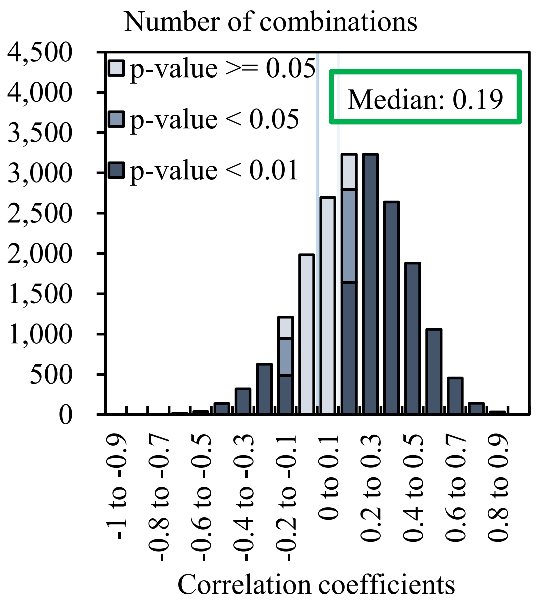
<Frequency of price decreases>



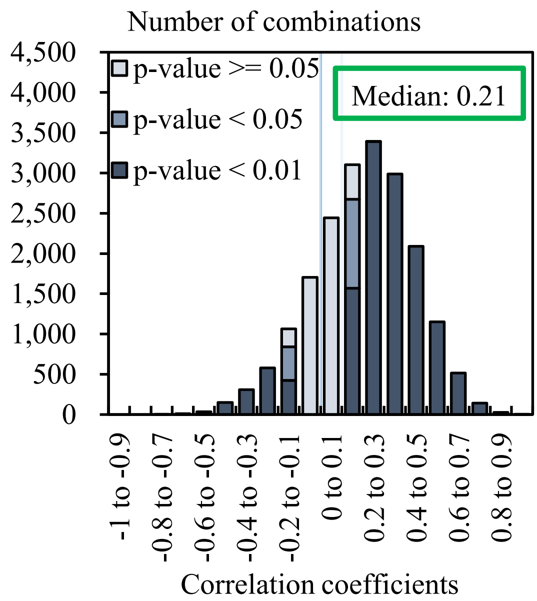
Notes: The panels plot the median of the average seasonal component of frequency of price changes across all categories. The shaded area indicates the 25th and 75th percentile bands.

Figure 6: Correlation of Frequency of Price Changes

(a) Correlation of frequency of price increases



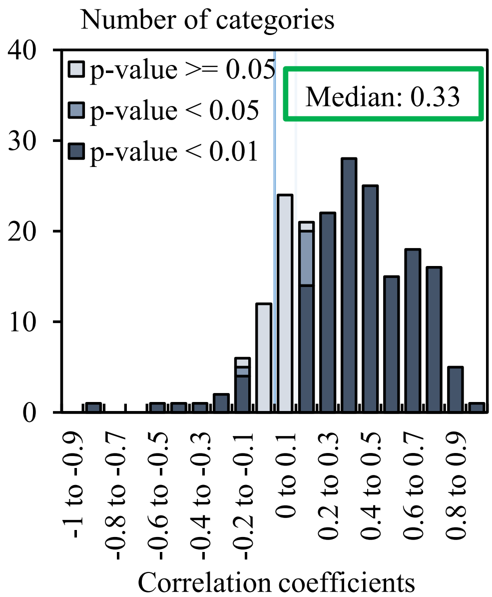
(b) Correlation of frequency of price decreases



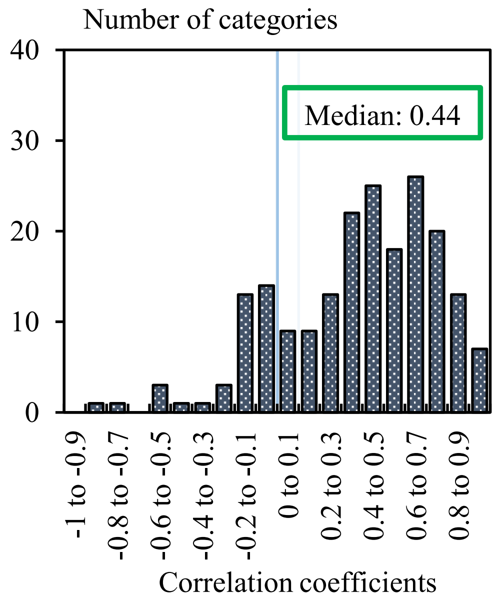
Notes: The panels show histograms of the correlations of the seasonal components of (a)frequency of price increases and (b)frequency of price decreases across pairs of 199 categories, respectively. The data coverage is 1990 to 2021, excluding 2003 and 2004.

(c) Correlation between frequency of price increases and frequency of price decreases

<Pearson's correlation>



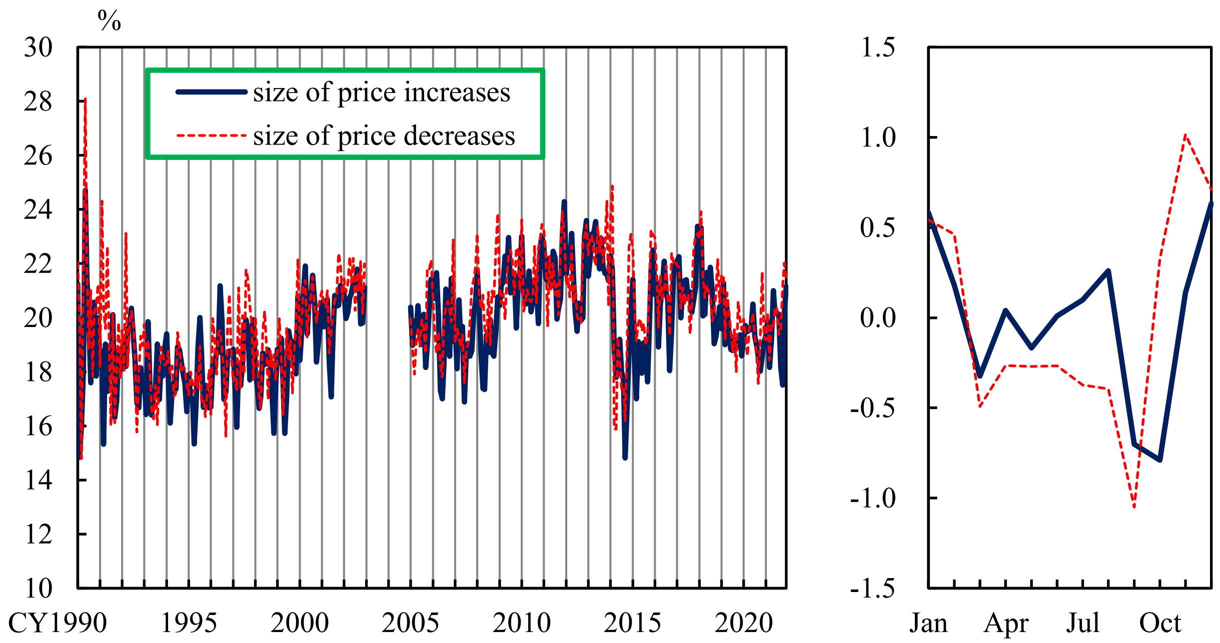
<Spearman's rank correlation>



Notes: The panels show histograms of the correlations between the seasonal components of the frequency of price increases and price decreases within the same category. The data coverage is 1990 to 2021, excluding 2003 and 2004. The left panel is based on Pearson's correlation coefficient. The right panel is based on Spearman's rank coefficient, calculated using the average seasonal component.

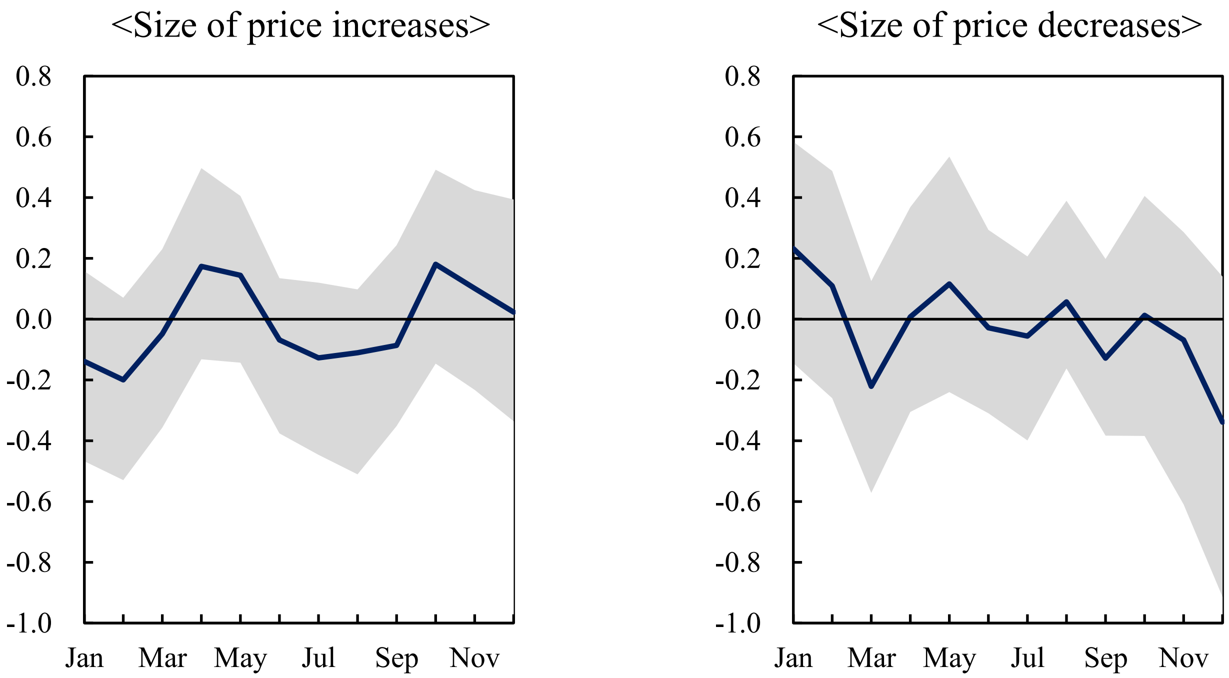
Figure 7: Size of Price Changes

(a) Category "soybean curd and its products, Tofu"



Notes: The left panel plots the size of price changes of the category "soybean curd and its products." The right panel shows the average seasonal component of the size of price increases and price decreases.

(b) Seasonal component across all categories

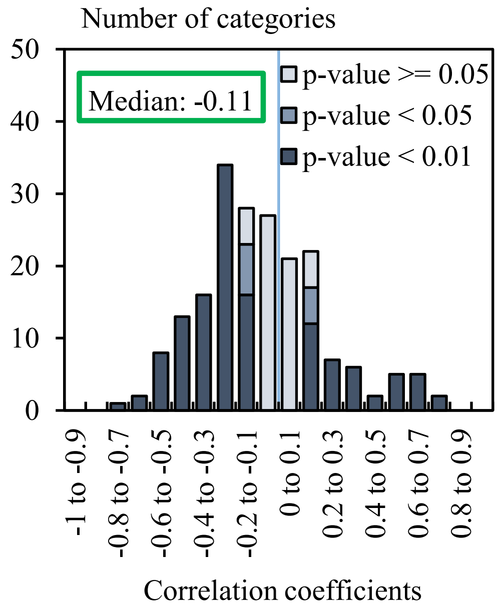


Notes: The panels plot the median of the average seasonal component of the size of price changes across all categories. The shaded area indicates the 25th and 75th percentile bands.

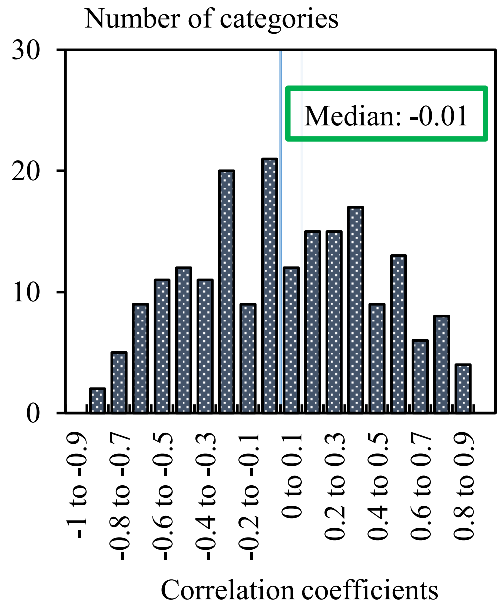
Figure 8: Correlation between Frequency and Size of Price Changes

(a) Correlation between frequency of price increases and size of price increases

<Pearson's correlation>

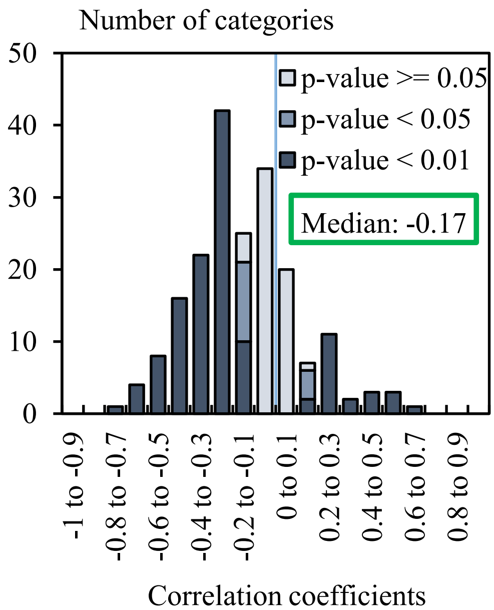


<Spearman's rank correlation>

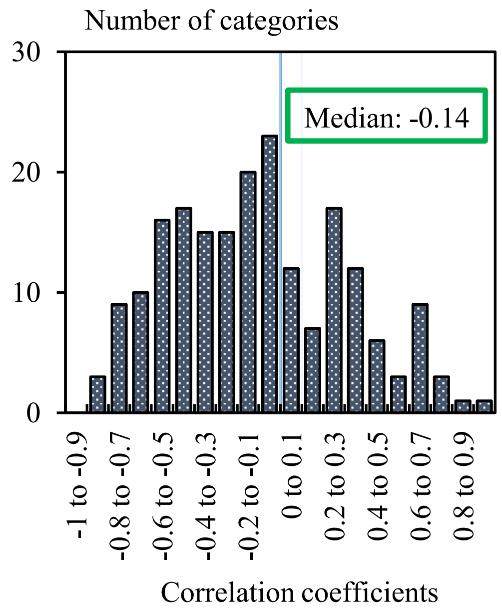


(b) Correlation between frequency of price decreases and size of price decreases

<Pearson's correlation>



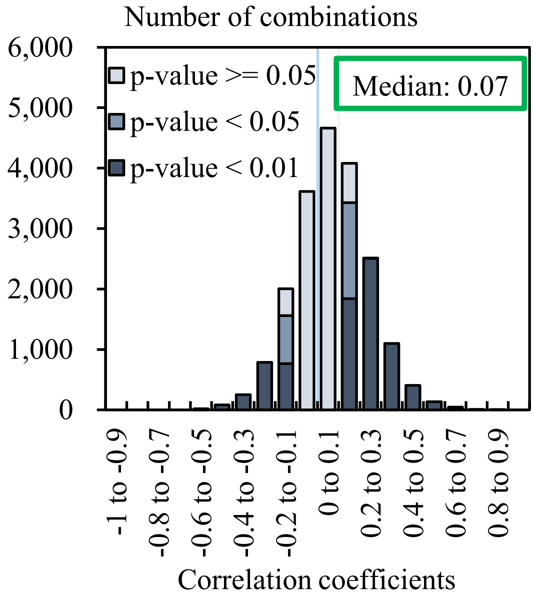
<Spearman's rank correlation>



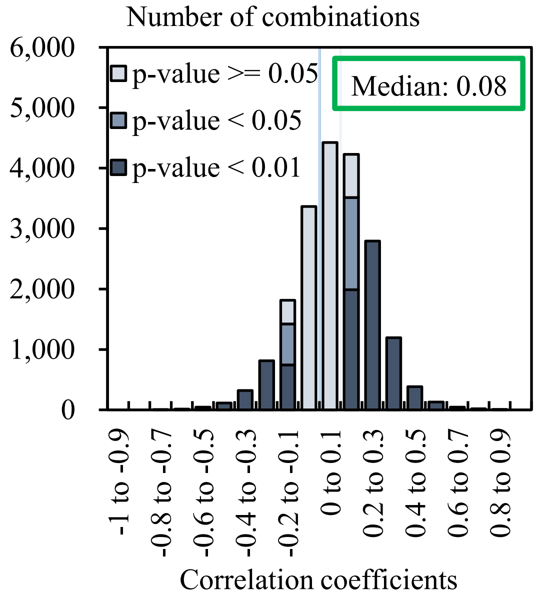
Notes: The panels show the histogram of the correlations between the seasonal component of the frequency of price increases (decreases) and the size of price increases (decreases) for all 199 categories. The data coverage is 1990 to 2021, excluding 2003 and 2004. The left panel is based on Pearson's correlation coefficient. The right panel is based on Spearman's rank correlation, calculated using the average seasonal component.

Figure 9: Correlation of Size of Price Changes

(a) Correlation of size of price increases



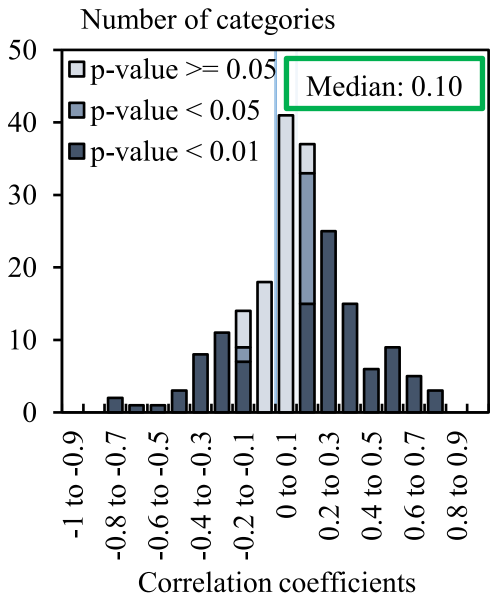
(b) Correlation of size of price decreases



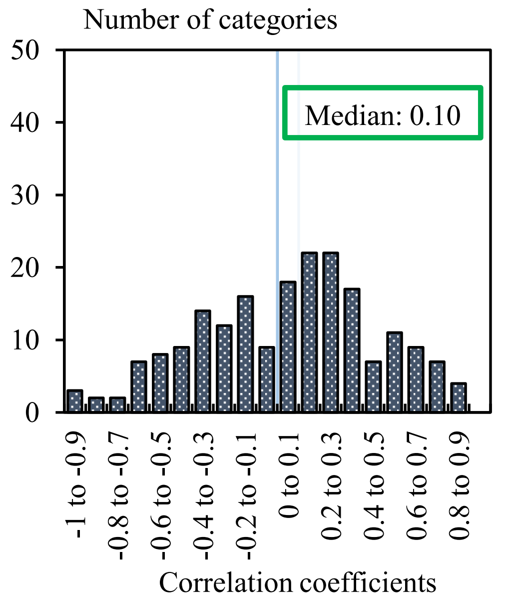
Notes: The panels show histograms of the correlations of the seasonal component of (a)size of price increases and (b)size of price decreases across pairs of 199 categories, respectively. The data coverage is 1990 to 2021, excluding 2003 and 2004.

(c) Correlation between size of price increases and size of price decreases

<Pearson's correlation>



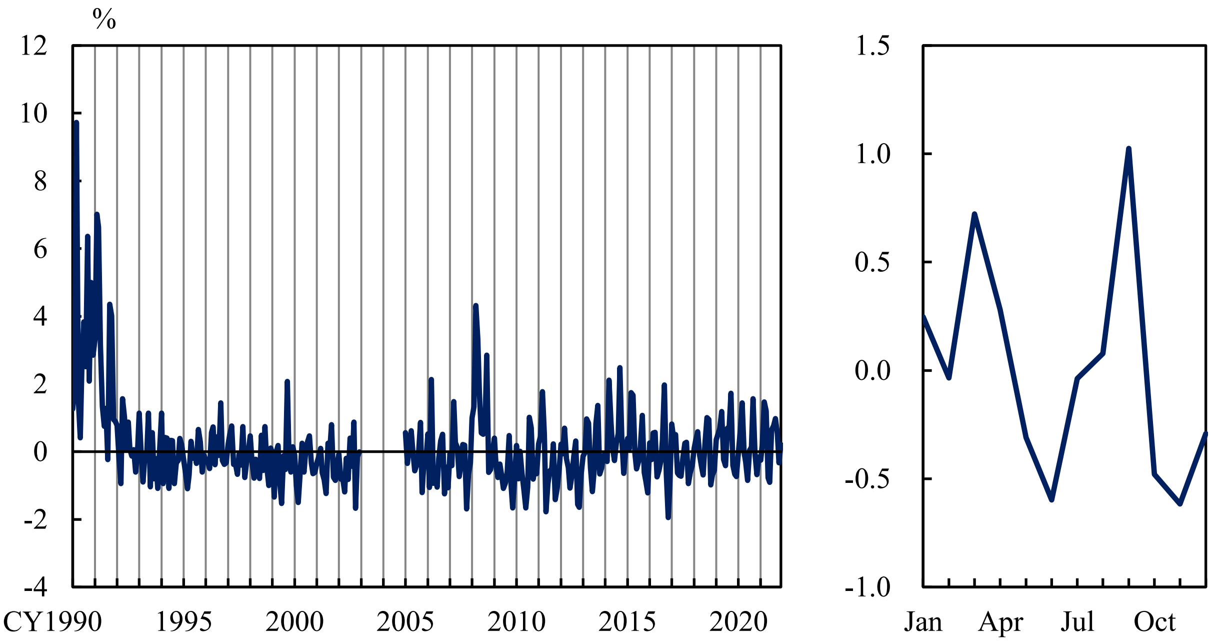
<Spearman's rank correlation>



Notes: The panels show histograms of the correlations between the seasonal component of the size of price increases and price decreases within the same category. The data coverage is 1990 to 2021, excluding 2003 and 2004. The left panel is based on Pearson's correlation coefficients. The right panel is based on Spearman's rank correlation, calculated using the average seasonal component.

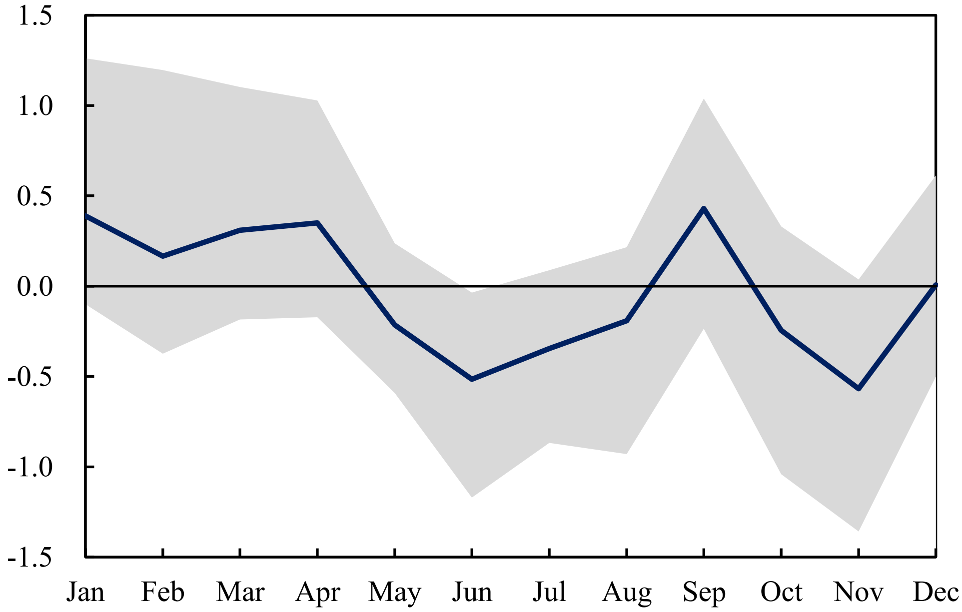
Figure 10: POS Inflation Rate

(a) Category "soybean curd and its products, Tofu"



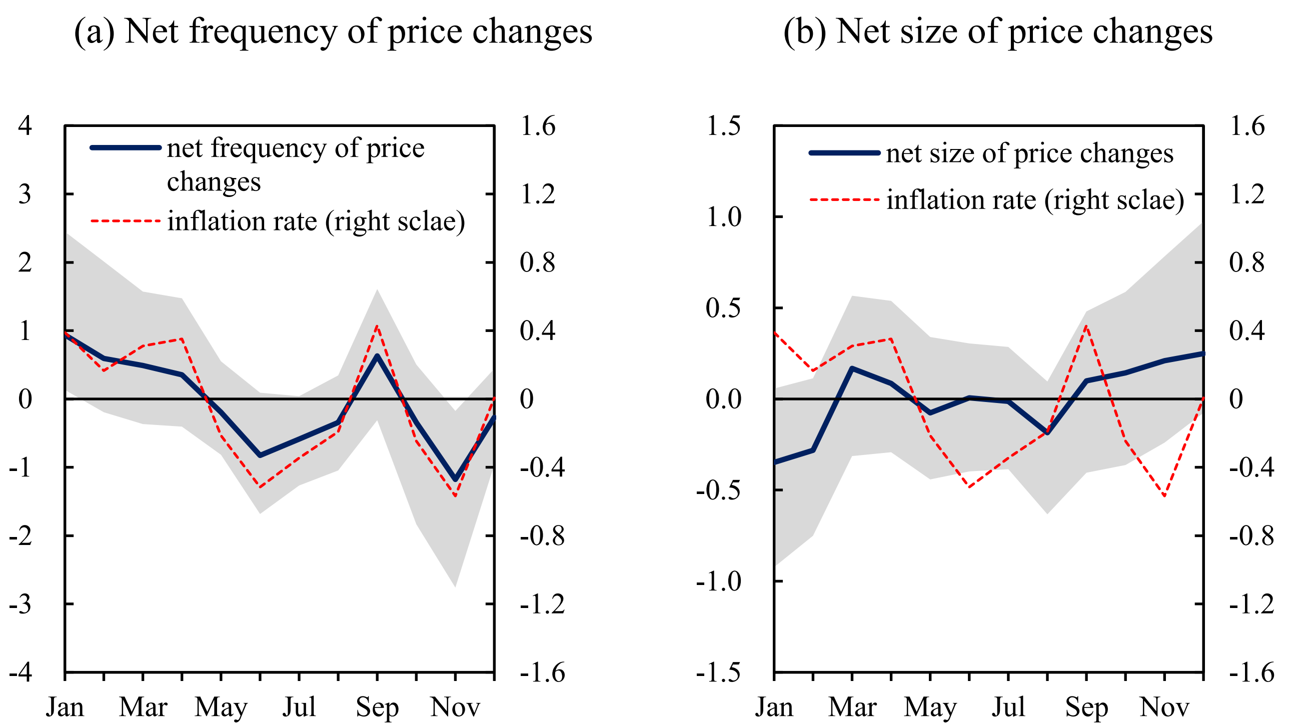
Notes: The left panel plots the POS inflation rate of the category "soybean curd and its products." The right panel shows the average seasonal component of the POS inflation rate.

(b) Seasonal component across all categories



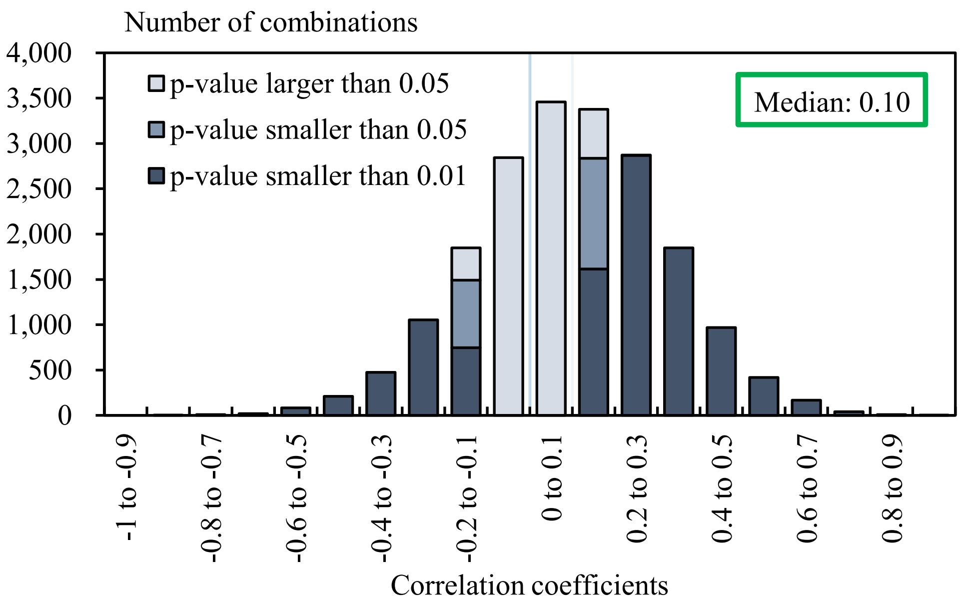
Notes: The panel plots the median of the average seasonal component of the POS inflation rate across all categories. The shaded area indicates the 25th and 75th percentile bands.

Figure 11: 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.

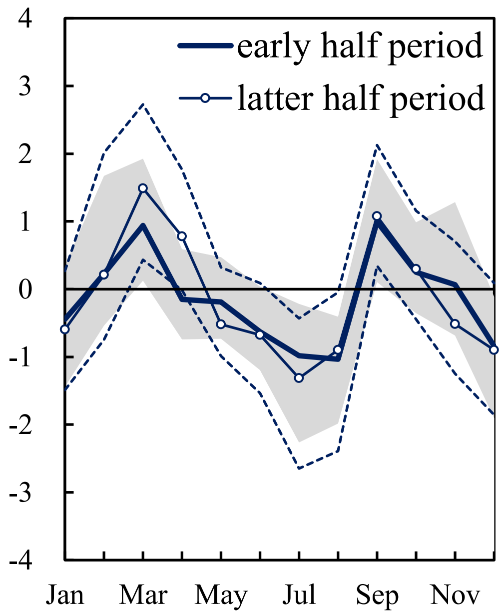
Figure 12: Correlation of POS Inflation Rate across Categories



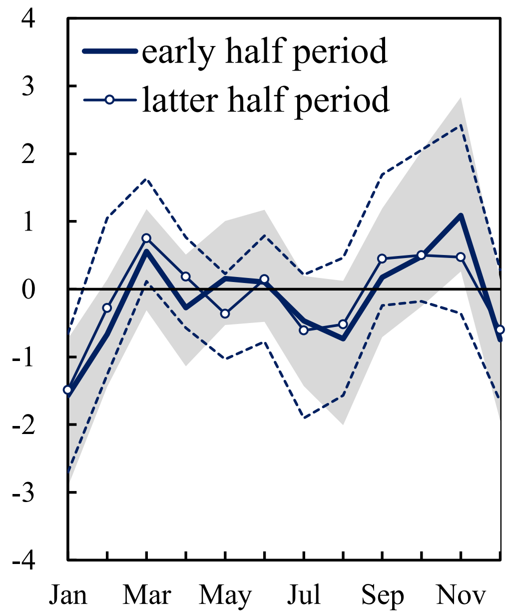
Notes: The plot shows the histogram for the correlations of the seasonal component of the POS inflation rate across pairs of 199 categories. The data coverage is 1990 to 2021, excluding 2003 and 2004.

Figure 13: Seasonality in the Two Subsample Periods

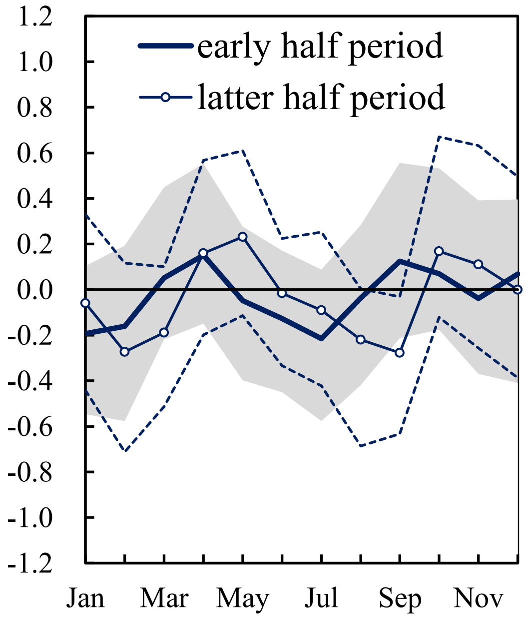
(a) Frequency of price increases



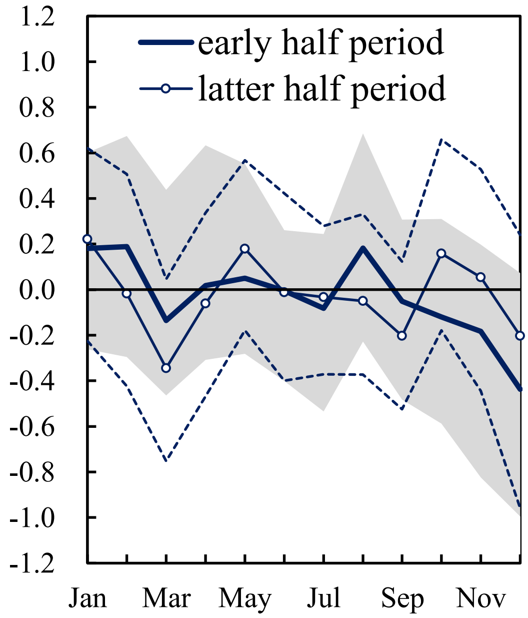
(b) Frequency of price decreases



(c) Size of price increases



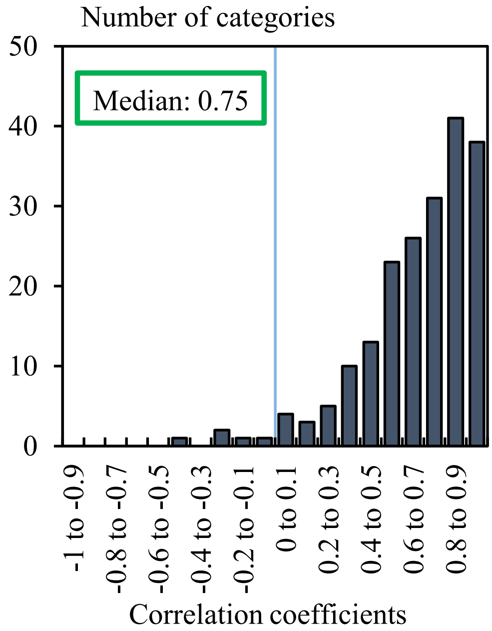
(d) Size of price decreases



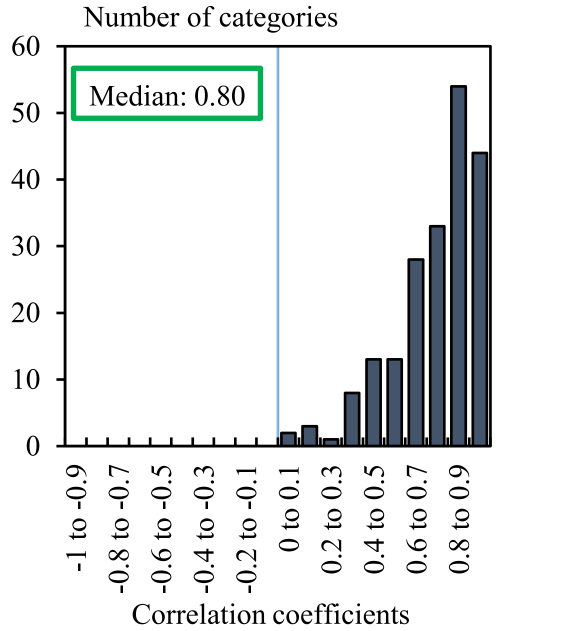
Notes: The panels plot the average seasonal component in the early and the latter halves of the sample period for each category. The solid line and circle marker indicate the median of all categories. The shaded area and dotted line indicate the 25th and 75th percentile bands.

Figure 14: Correlation of Seasonality between the Two Subsample Periods

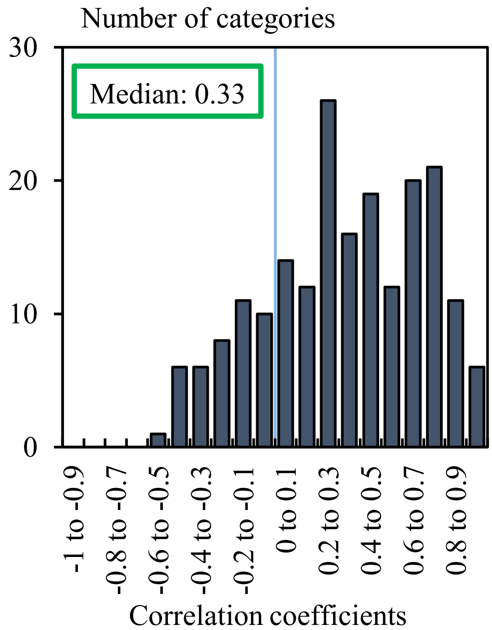
(a) Frequency of price increases



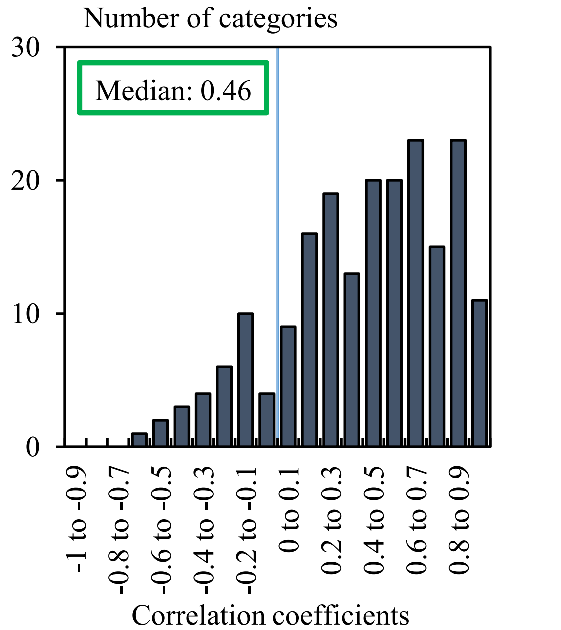
(b) Frequency of price decreases



(c) Size of price increases



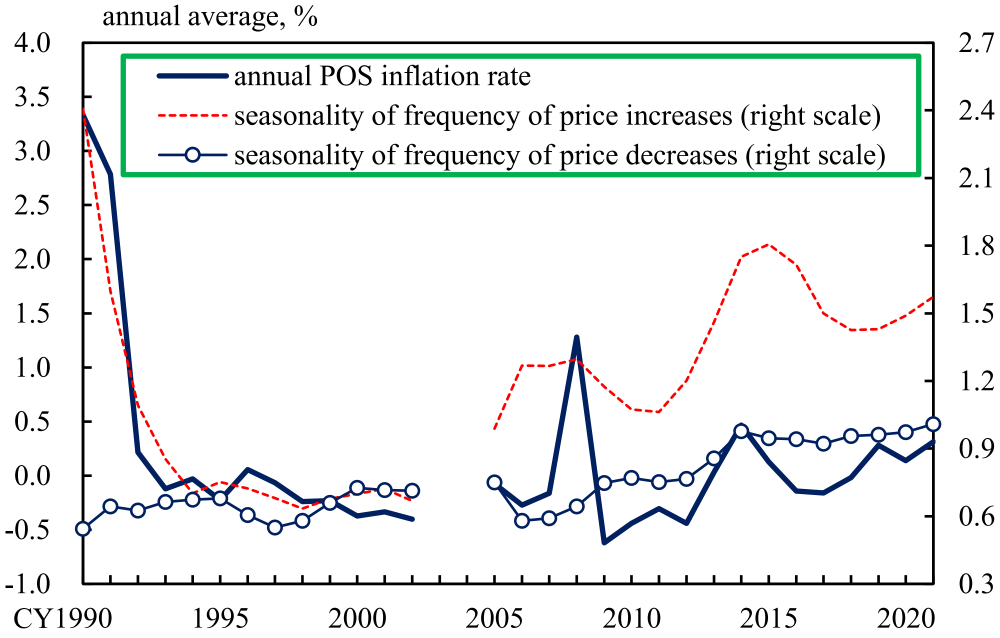
(d) Size of price decreases



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. The data coverage is 1990 to 2021, excluding 2003 and 2004.

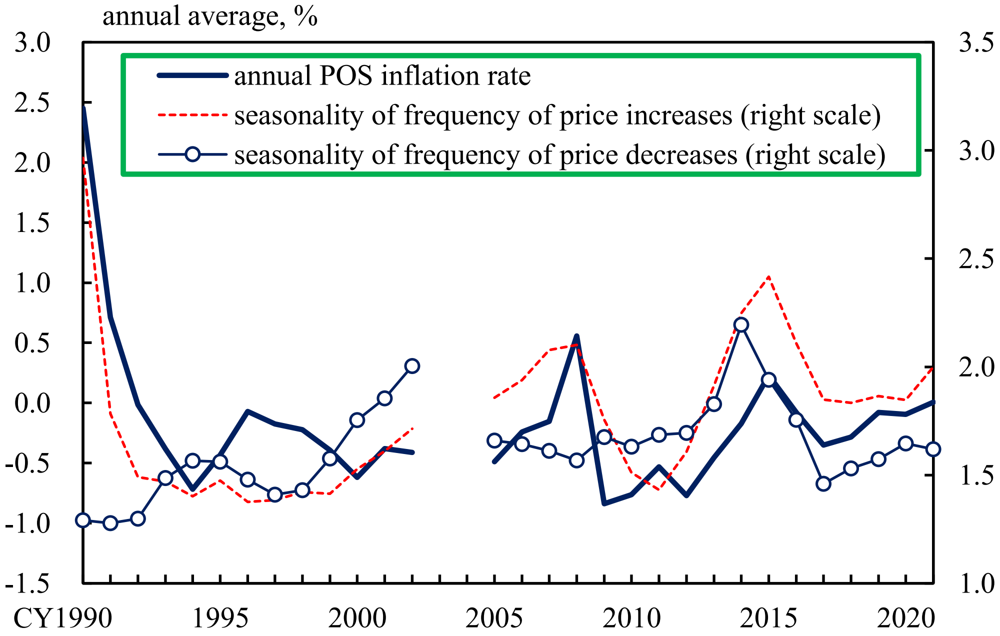
Figure 15: Annual Inflation and Seasonality of Frequency of Price Changes

(a) Category "soybean curd and its products, Tofu"



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.

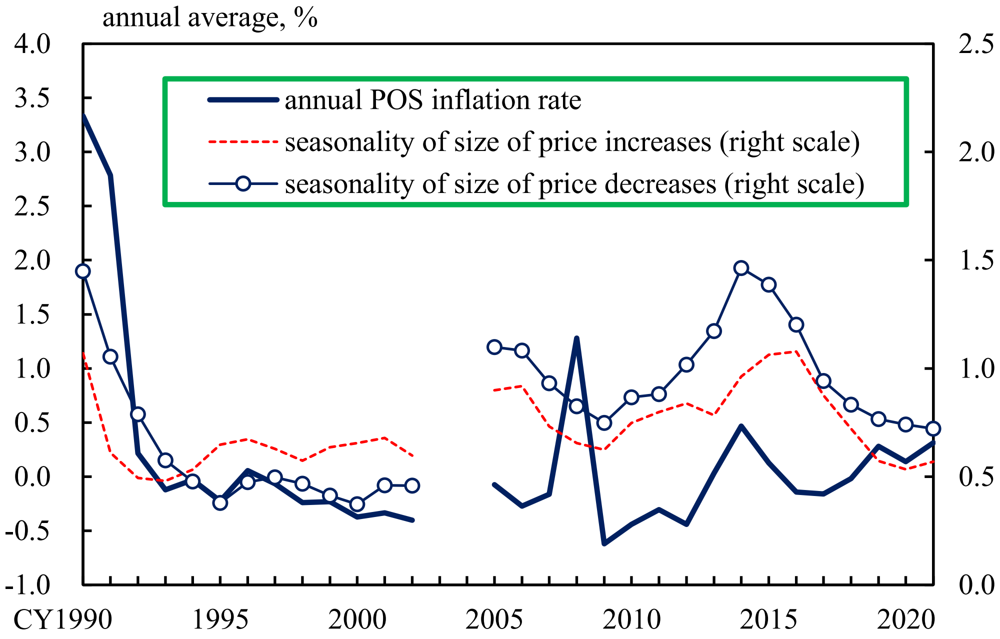
(b) Median of all categories



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.

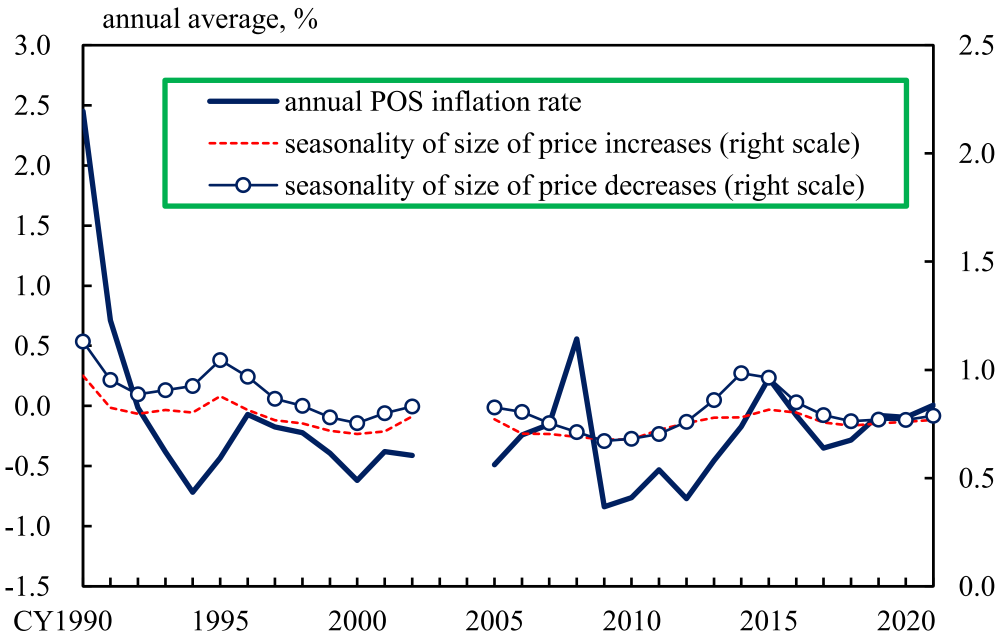
Figure 16: Annual Inflation and Seasonality of Size of Price Changes

(a) Category "soybean curd and its products, Tofu"



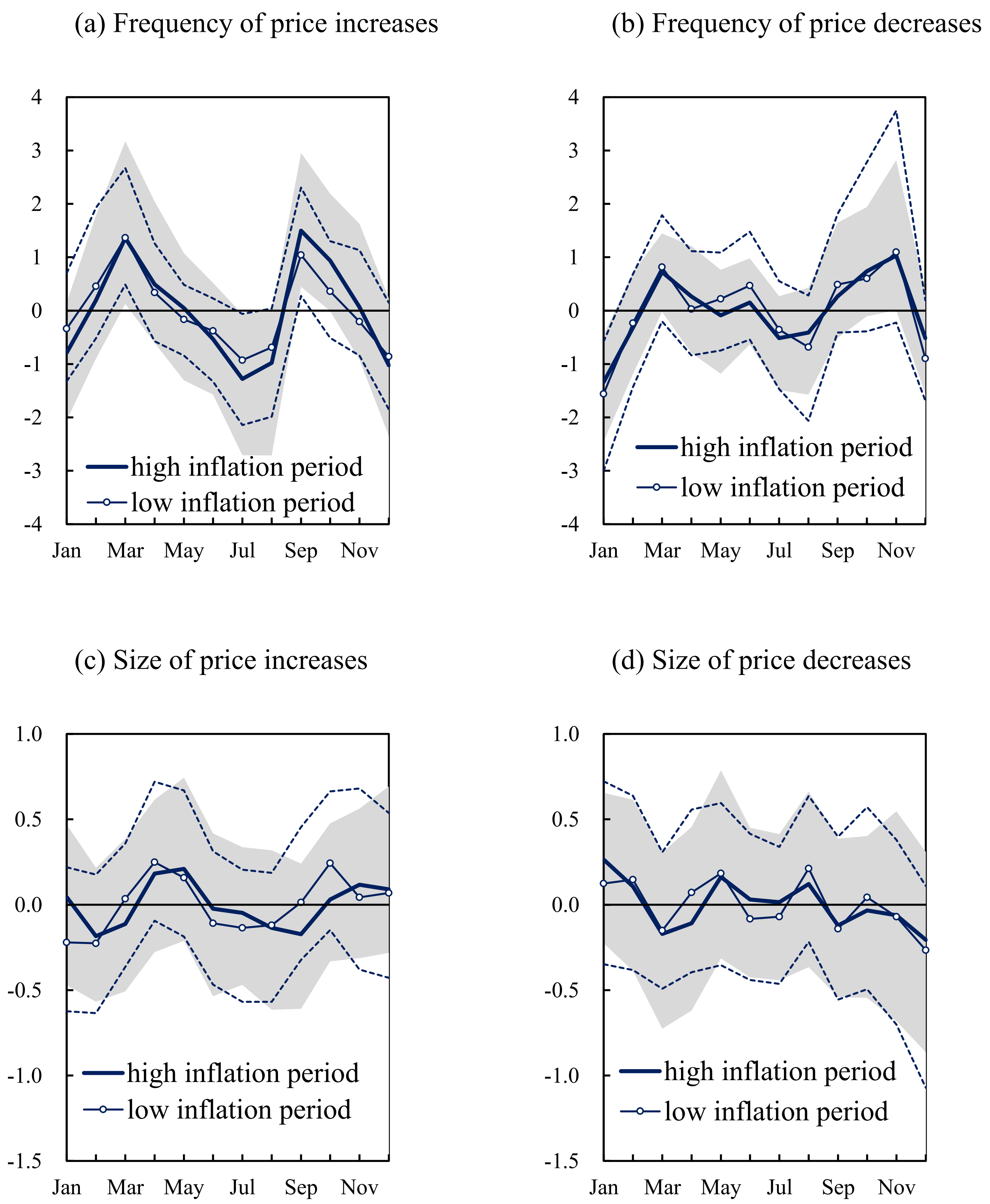
Notes: Annual POS inflation rate is the annual average of the monthly inflation rate. The dotted line and the solid line with circle marker indicate the standard deviation of the seasonal component of the size of price increases and price decreases during the year, respectively.

(b) Median of all categories



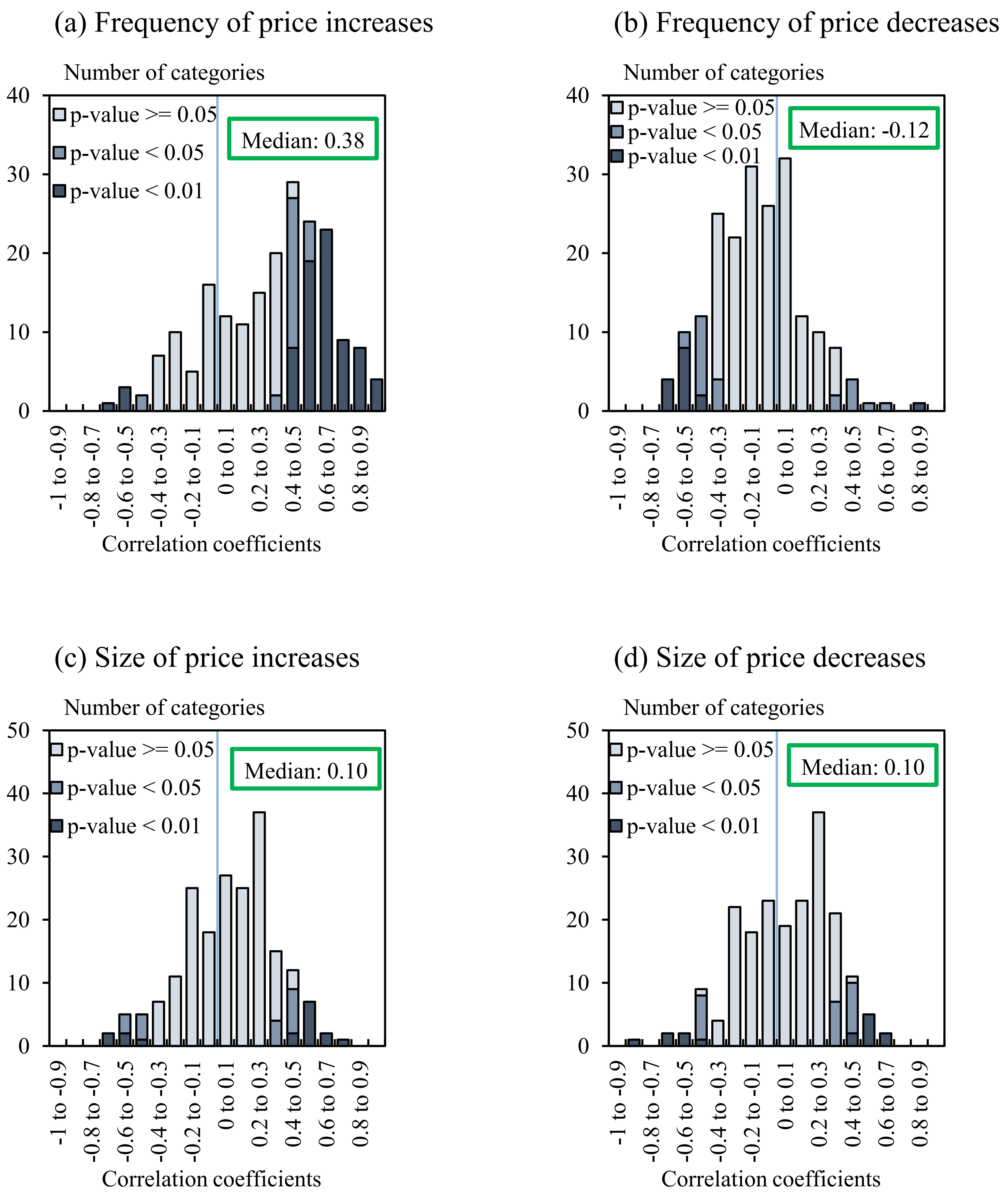
Notes: Annual POS inflation rate is the annual average of the monthly inflation rate. The dotted line and the solid line with circle marker indicate the standard deviation of the seasonal component of the size of price increases and price decreases during the year, respectively. For all categories, the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

Figure 17: Seasonality in High and Low Inflation Periods



Notes: The panels plot the average seasonal component in the high and the low inflaton 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.

Figure 18: Correlation between Seasonality of Price Changes and Annual POS Inflation

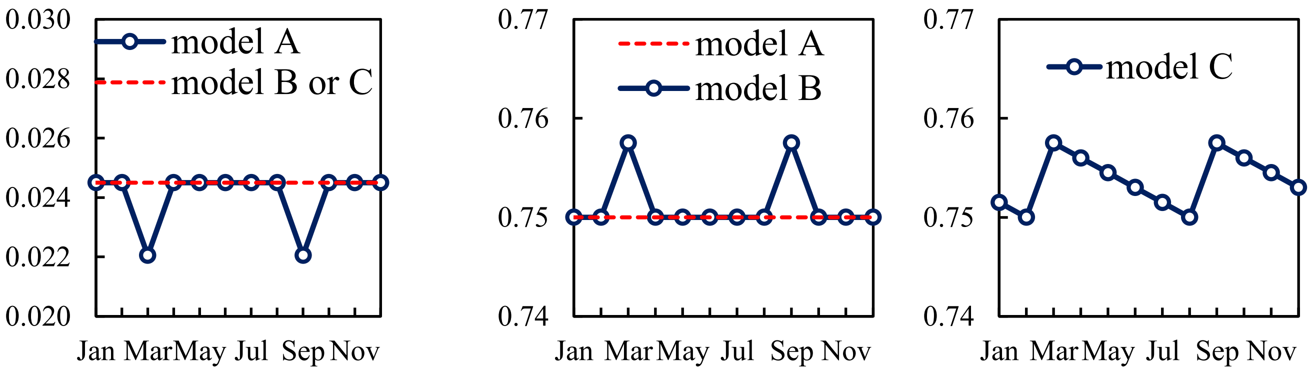


Notes: These panels show histograms of the correlations between the annual POS inflation rate and the standard deviation of the seasonal components for (a)the frequency of price increases, (b)the frequency of price decreases, (c)the size of price increases, and (d)the size of price decreases during the year, respectively. The data coverage is 1990 to 2021, excluding 2003 and 2004.

Figure 19: Model Parameters

(a) Parameters with seasonality

< K (size of menu cost) >   < ω (real marginal cost) >



(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

< Model A >   < Model B >   < Model C >

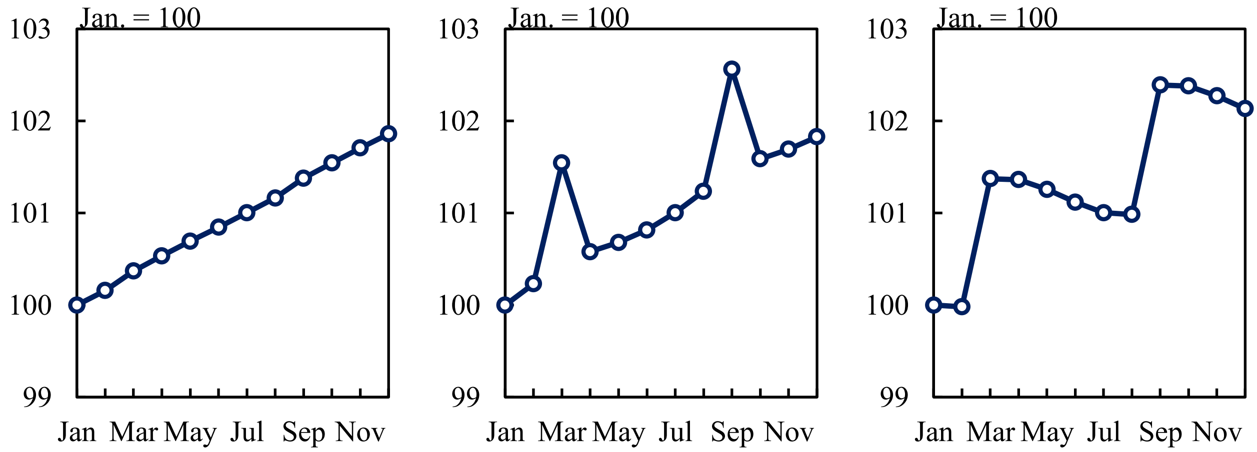
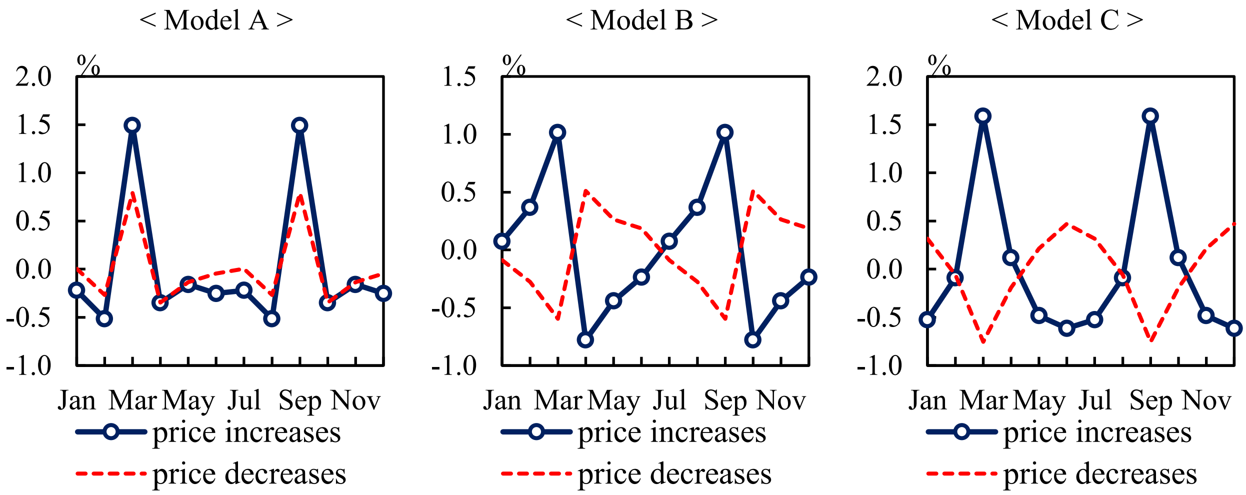


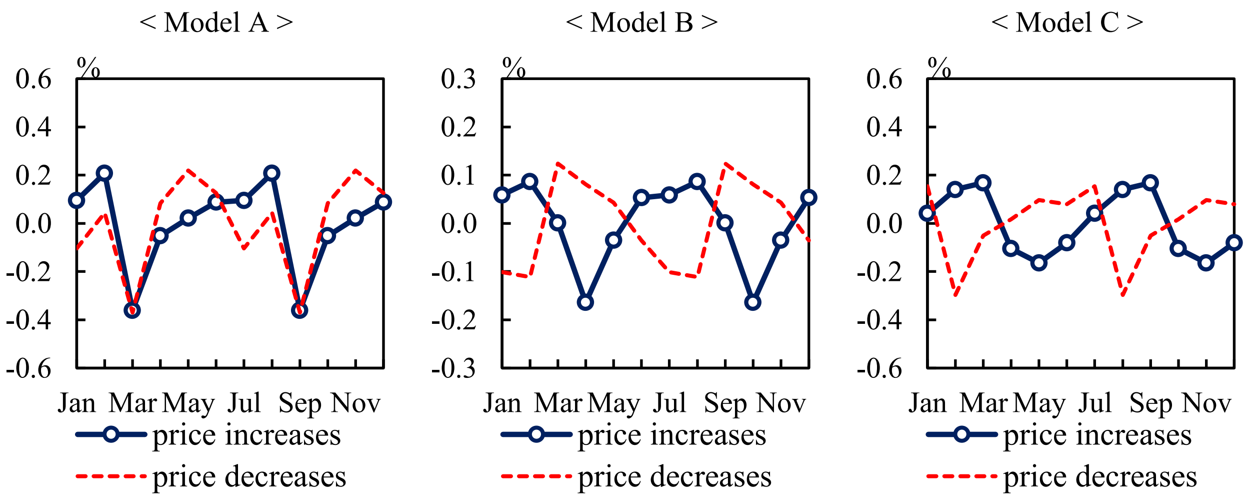
Figure 20: Seasonality of Price Changes in the Models

(a) Seasonality in the frequency of price changes



Notes: Each panel indicates the seasonality in the frequency 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.

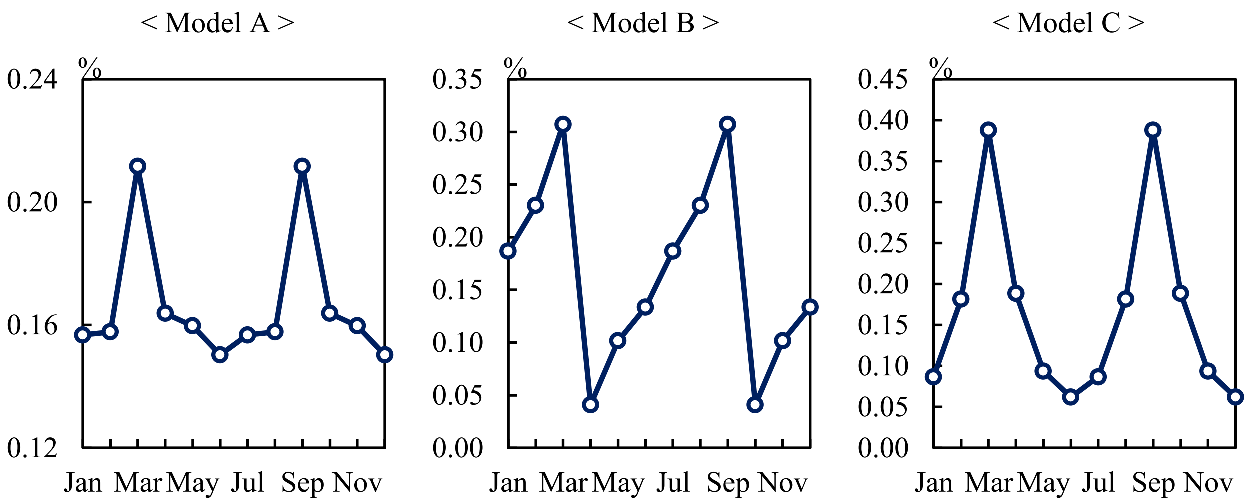
(b) Seasonality in the size of price changes



Notes: Each panel indicates the seasonality in 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.

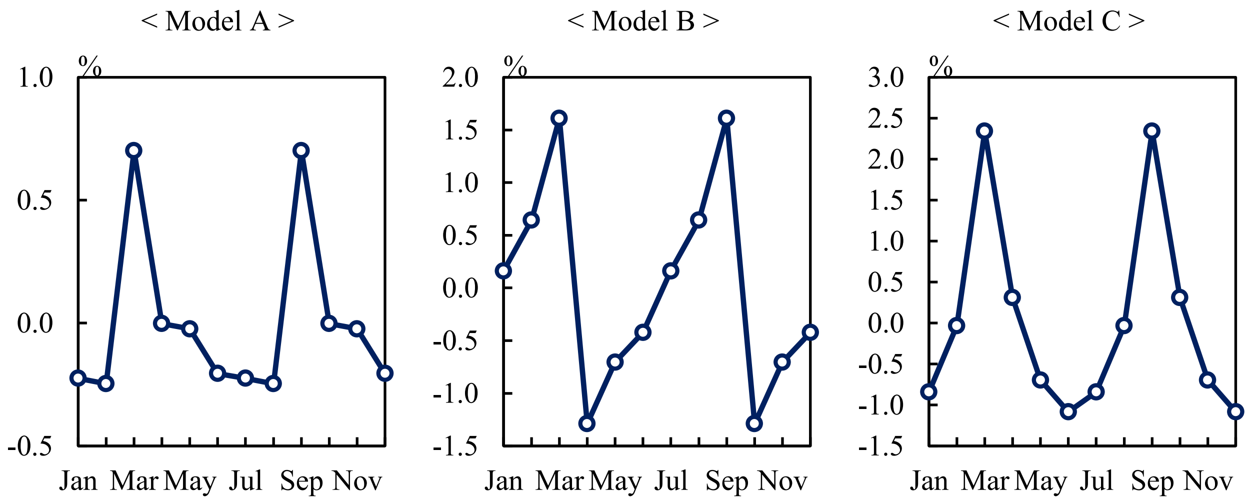
Figure 21: Seasonality of Inflation Rate in the Models

(a) Seasonality in the inflation rate



Notes: Each panel indicates the monthly inflation rate 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.

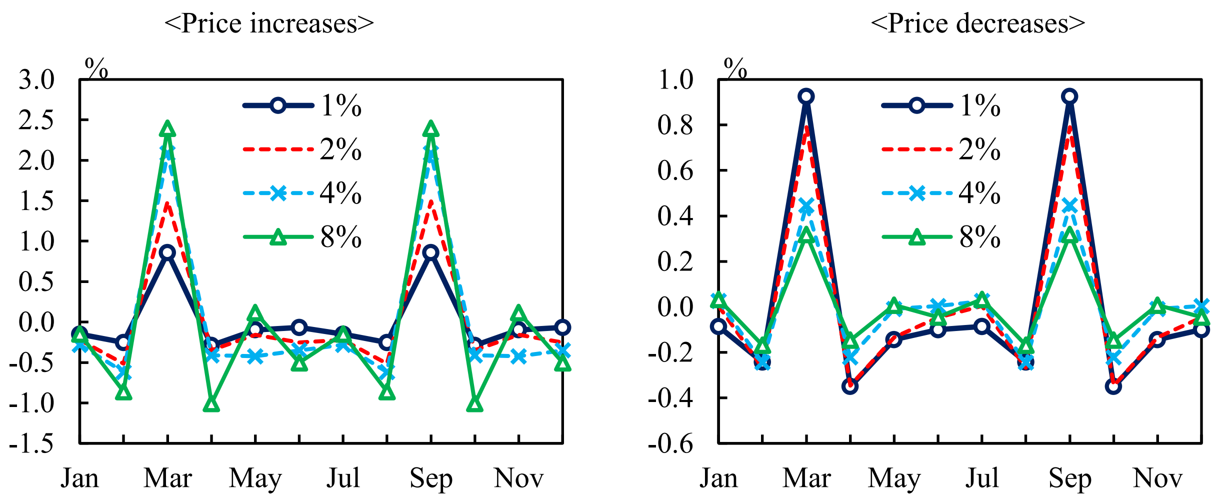
(b) Seasonality in the net frequency of price changes



Notes: Each panel indicates the monthly net frequency of price changes 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.

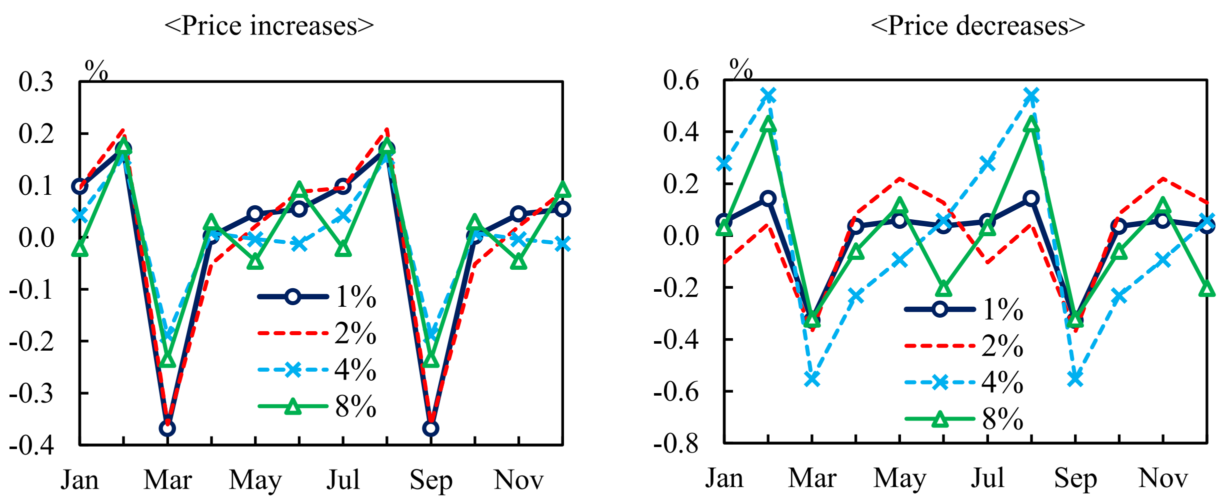
Figure 22: Seasonality and Inflation Rate in the Model A

(a) Frequency of price changes



Notes: Each panel indicates the seasonality in the frequency 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.

(b) Size of price changes

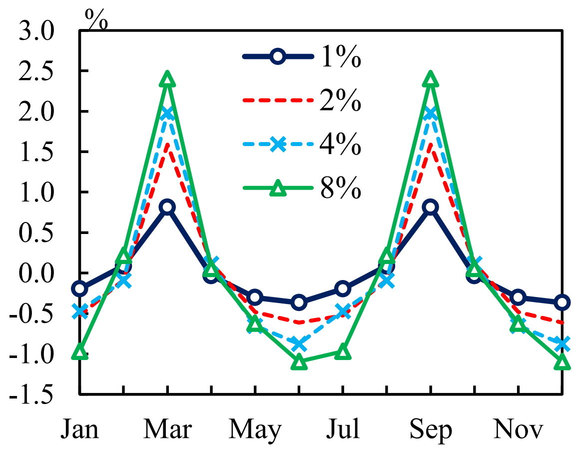


Notes: Each panel indicates the seasonality in the size of price increases and price decreases in model A for different annual inflation rates. The seasonality is obtained by subtracting the annual average from the corresponding series.

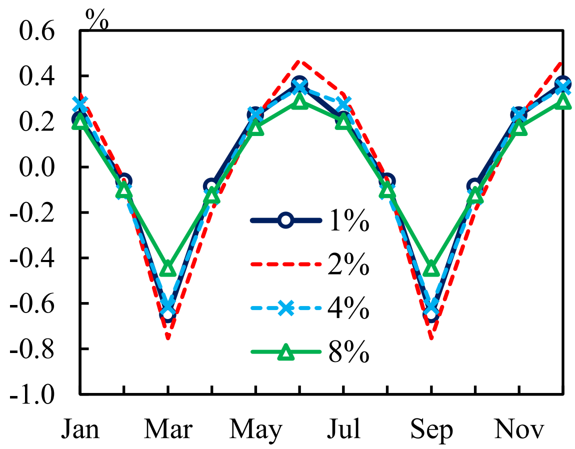
Figure 23: Seasonality and Inflation Rate in the Model C

(a) Frequency of price changes

<Price increases>



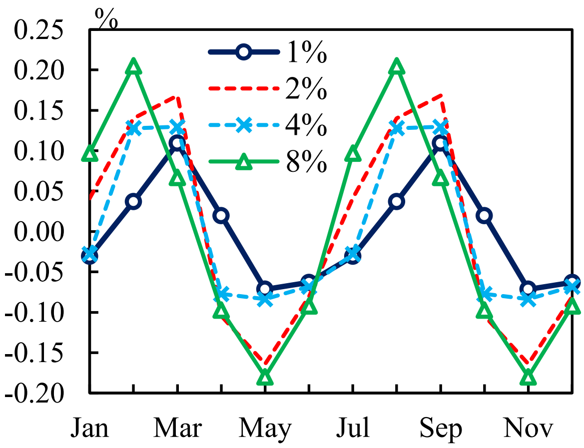
<Price decreases>



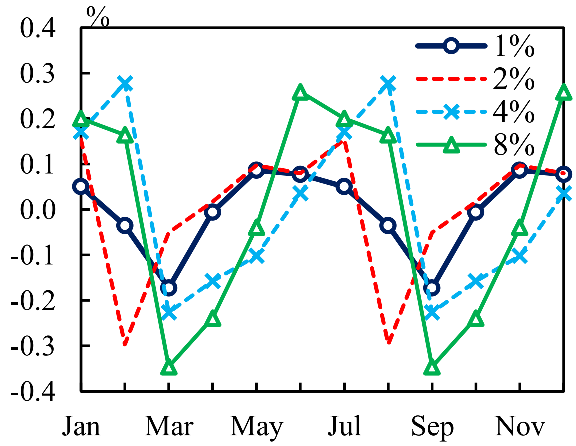
Notes: Each panel indicates the seasonality in the frequency of price increases and price decreases in model C for different annual inflation rates. The seasonality is obtained by subtracting the annual average from the corresponding series.

(b) Size of price changes

<Price increases>



<Price decreases>



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

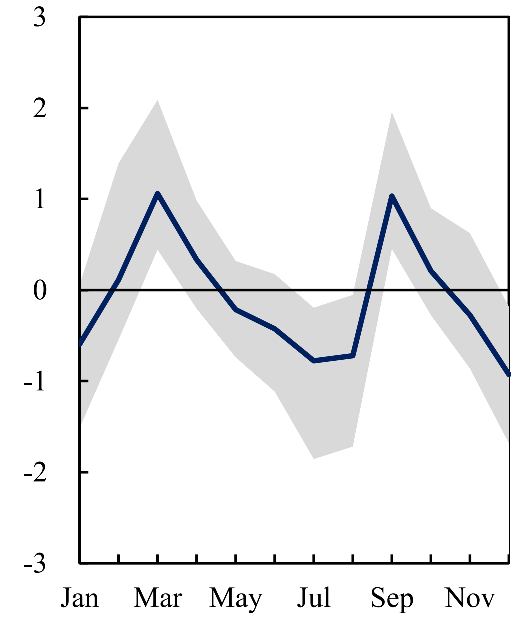
Table 1: Categories in the POS Data

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	

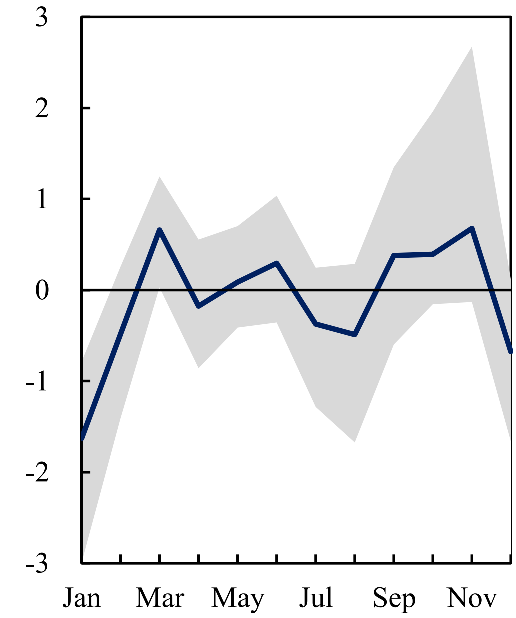
Note: The shaded area represents the categories of foods.

Figure B1: Seasonal Components of Price Changes Extracted by X12

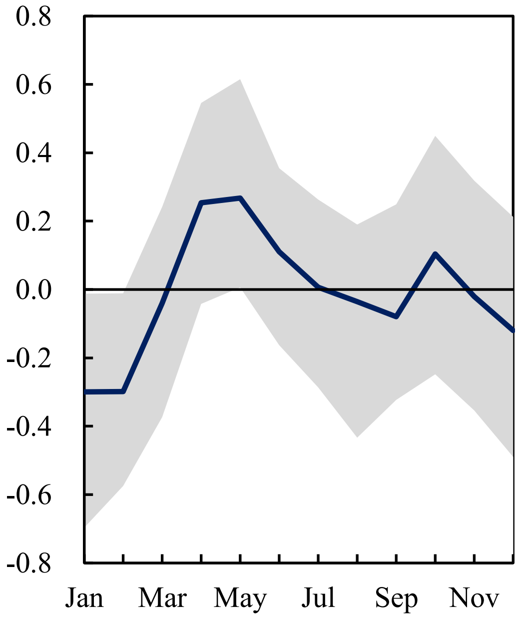
(a) Frequency of price increases



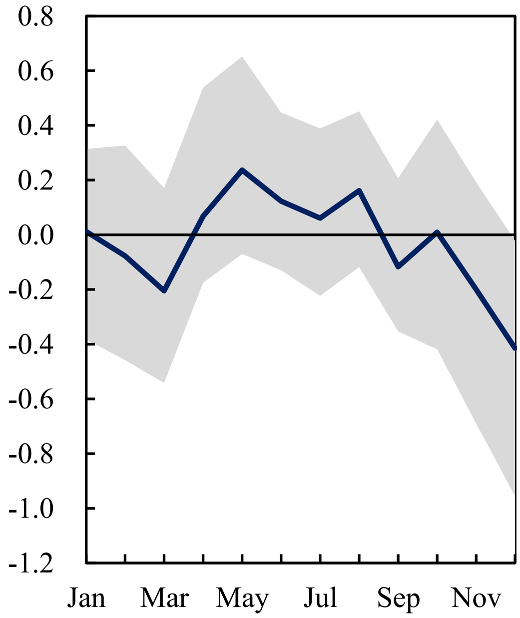
(b) Frequency of price decreases



(c) Size of price increases

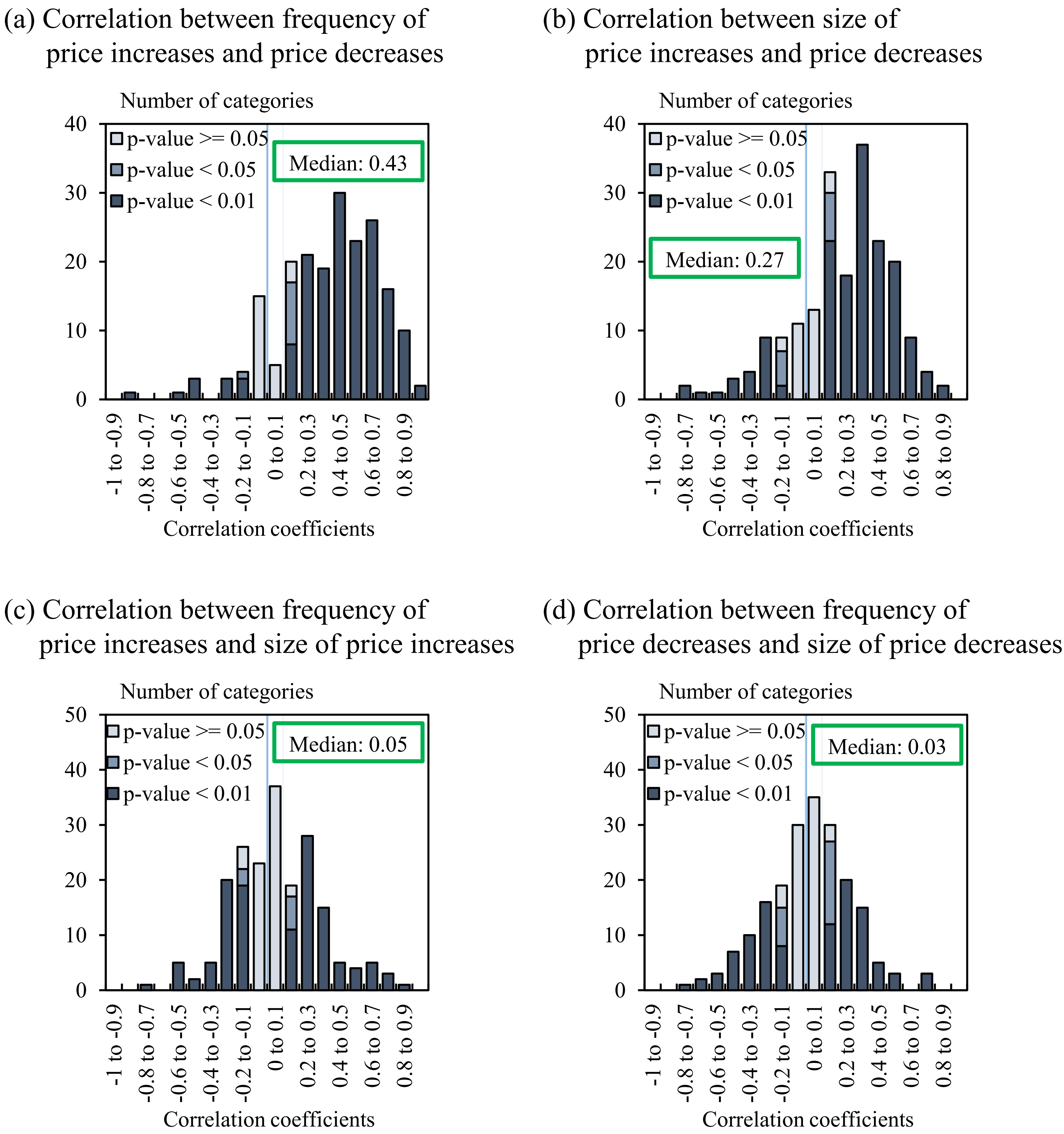


(d) Size of price decreases



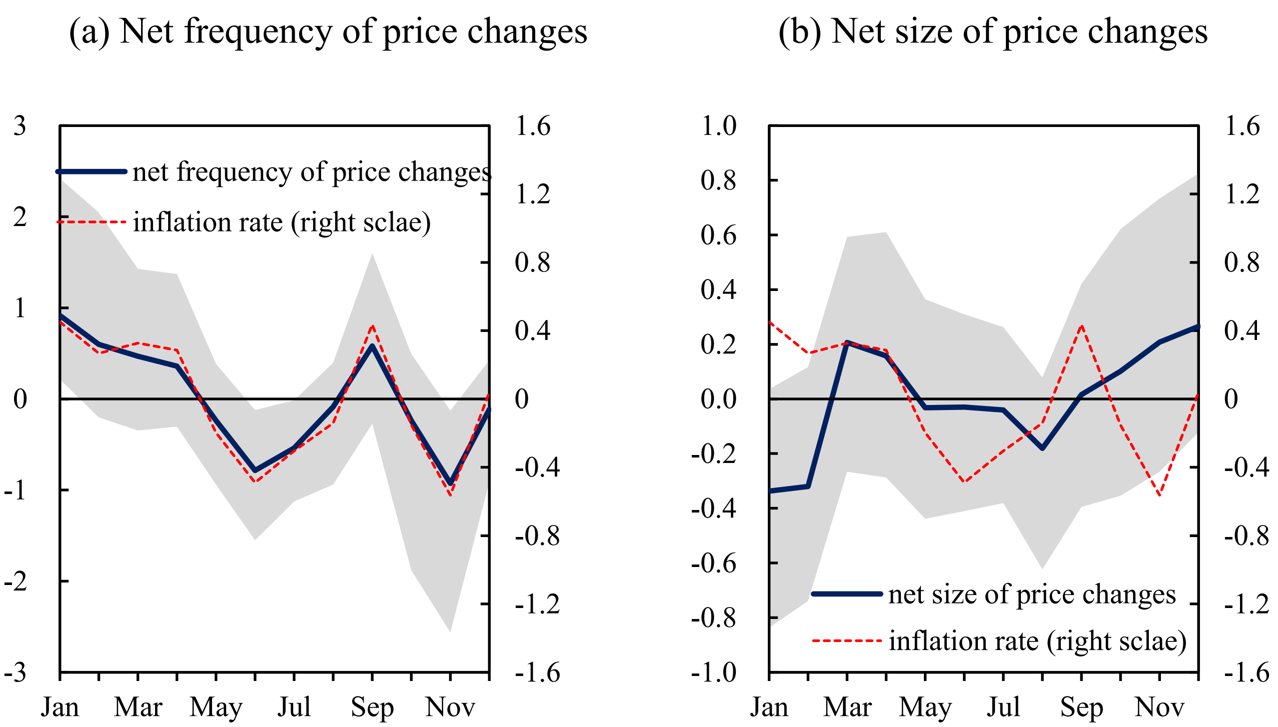
Notes: The panels plot the median of the average seasonal component of frequency and size of price changes across all categories. The shaded area indicates the 25th and 75th percentile bands. The seasonal components are extracted by X12.

Figure B2: Correlation of Seasonality of Frequency and Size of Price Changes Extracted by X12



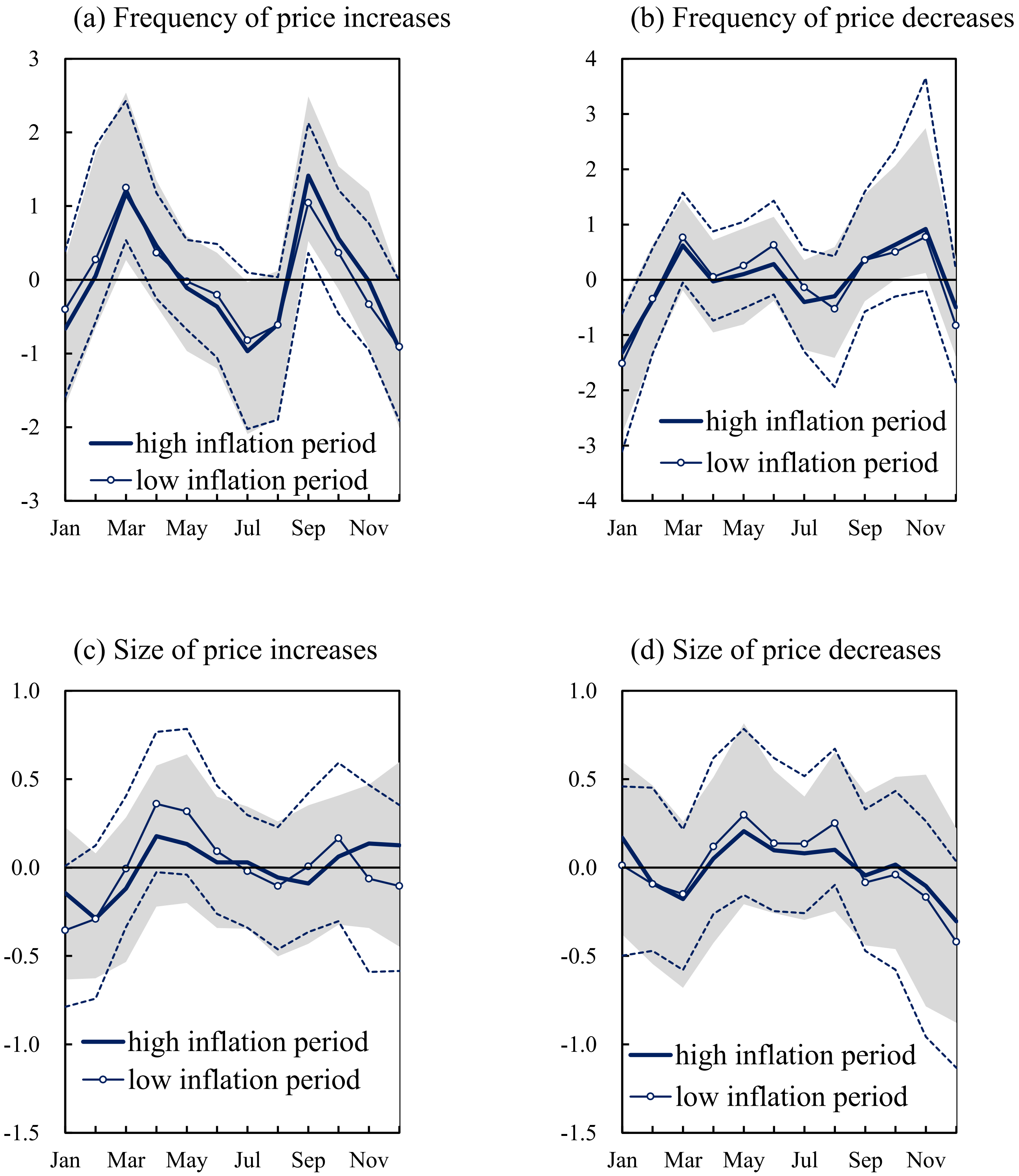
Notes: The panels show histograms of the correlation between the original series of (a)frequency of price increases and price decreases, (b)size of price increases and price decreases, (c)frequency of price increases and size of price increases and (d)frequency of price decreases and size of price decreases within the same category. The data coverage is 1990 to 2021, excluding 2003 and 2004. The seasonal components are extracted by X12.

Figure B3: 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.

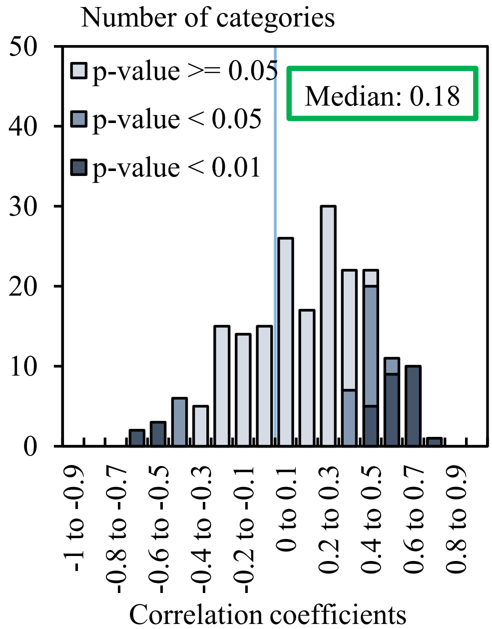
Figure B4: Seasonality in High and Low Inflation Periods Extracted by X12



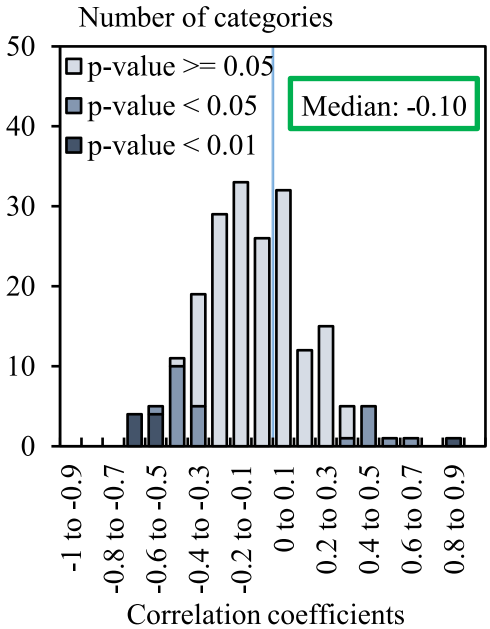
Notes: The panels plot the average seasonal component in the high and the low inflaton period for each of the categories. The solid line and that with circle marker indicate the median of all categories. The high inflation period is defined as all years in the top 10% of annual inflation during the whole 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 B5: Correlation between Annual POS Inflation and Seasonality of Price Changes Extracted by X12

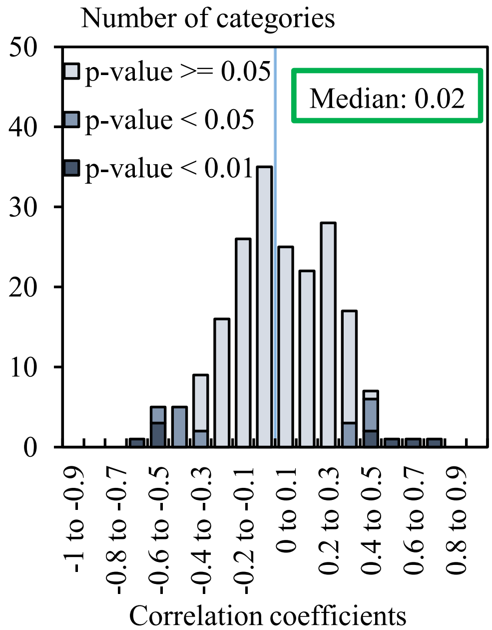
(a) Frequency of price increases



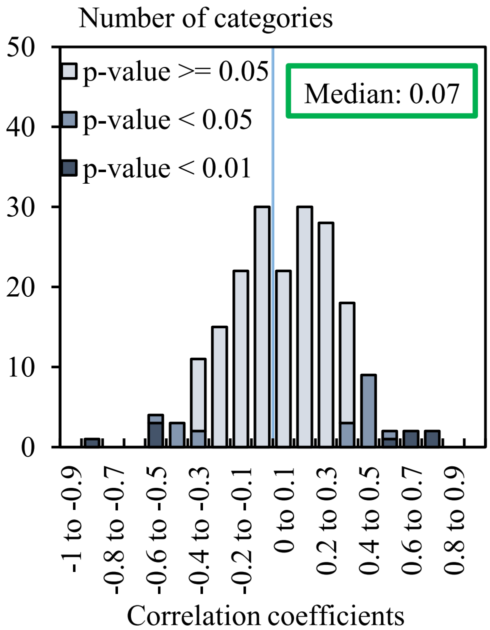
(b) Frequency of price decreases



(c) Size of price increases

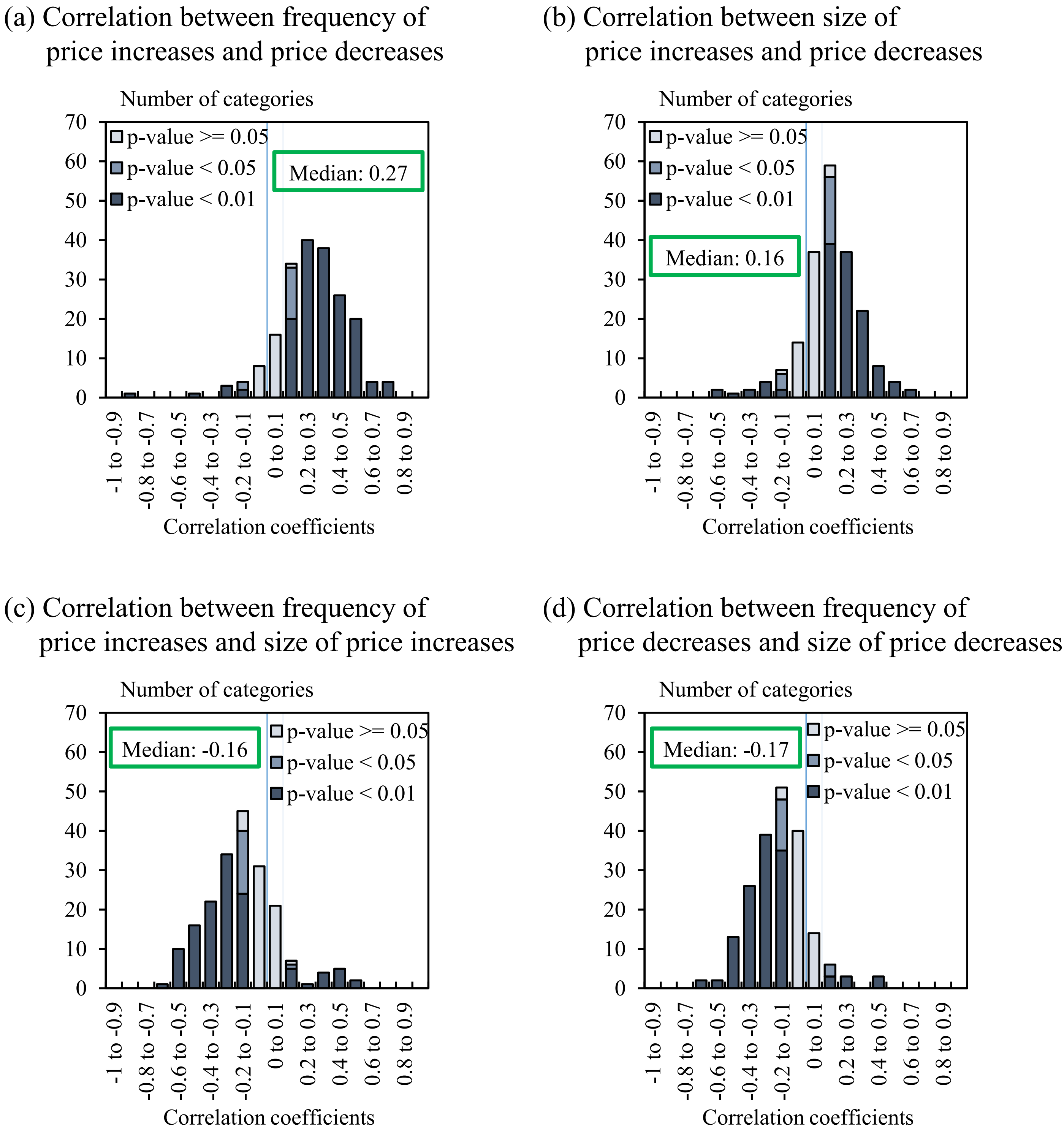


(d) Size of price decreases



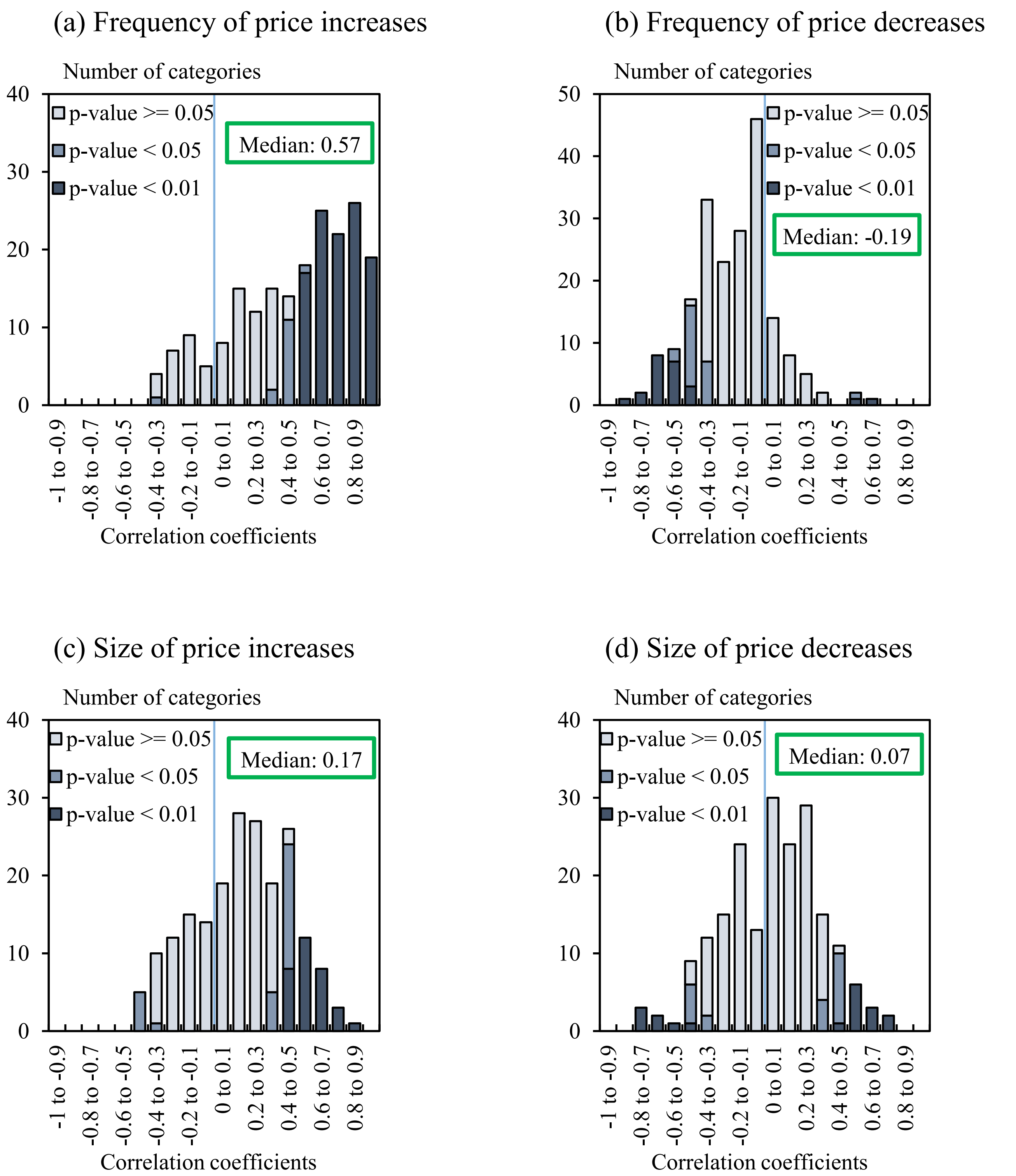
Notes: These panels show histograms of the correlation between the annual POS inflation rate and the standard deviation of the seasonal component of (a)the frequency of price increases, (b)the frequency of price decreases, (c)the size of price increases, and (d)the size of price decreases during the year, respectively, for all 199 categories. The data coverage is 1990 to 2021, excluding 2003 and 2004. The seasonal components are extracted by X12.

Figure C1: Correlation of Frequency and Size of Price Changes Extracted by Normalizing with the Annual Value



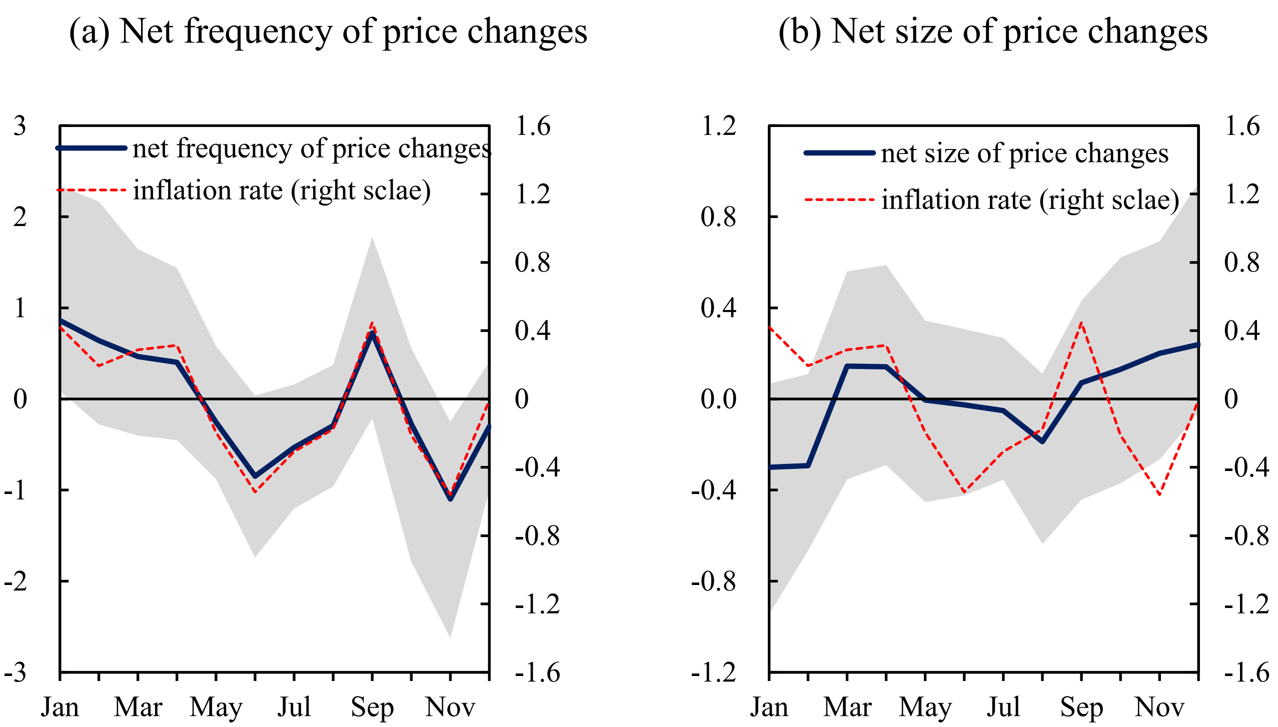
Notes: The panels show histograms of the correlation between the seasonal component of (a)frequency of price increases and price decreases, (b)size of price increases and price decreases, (c)frequency of price increases and size of price increases and (d)frequency of price decreases and size of price decreases within the same category. The data coverage is 1990 to 2021, excluding 2003 and 2004. The seasonal components are extracted by normalizing with the annual value.

Figure C2: Correlation between Annual POS Inflation and Seasonality of Price Changes Extracted by Normalizing with the Annual Value



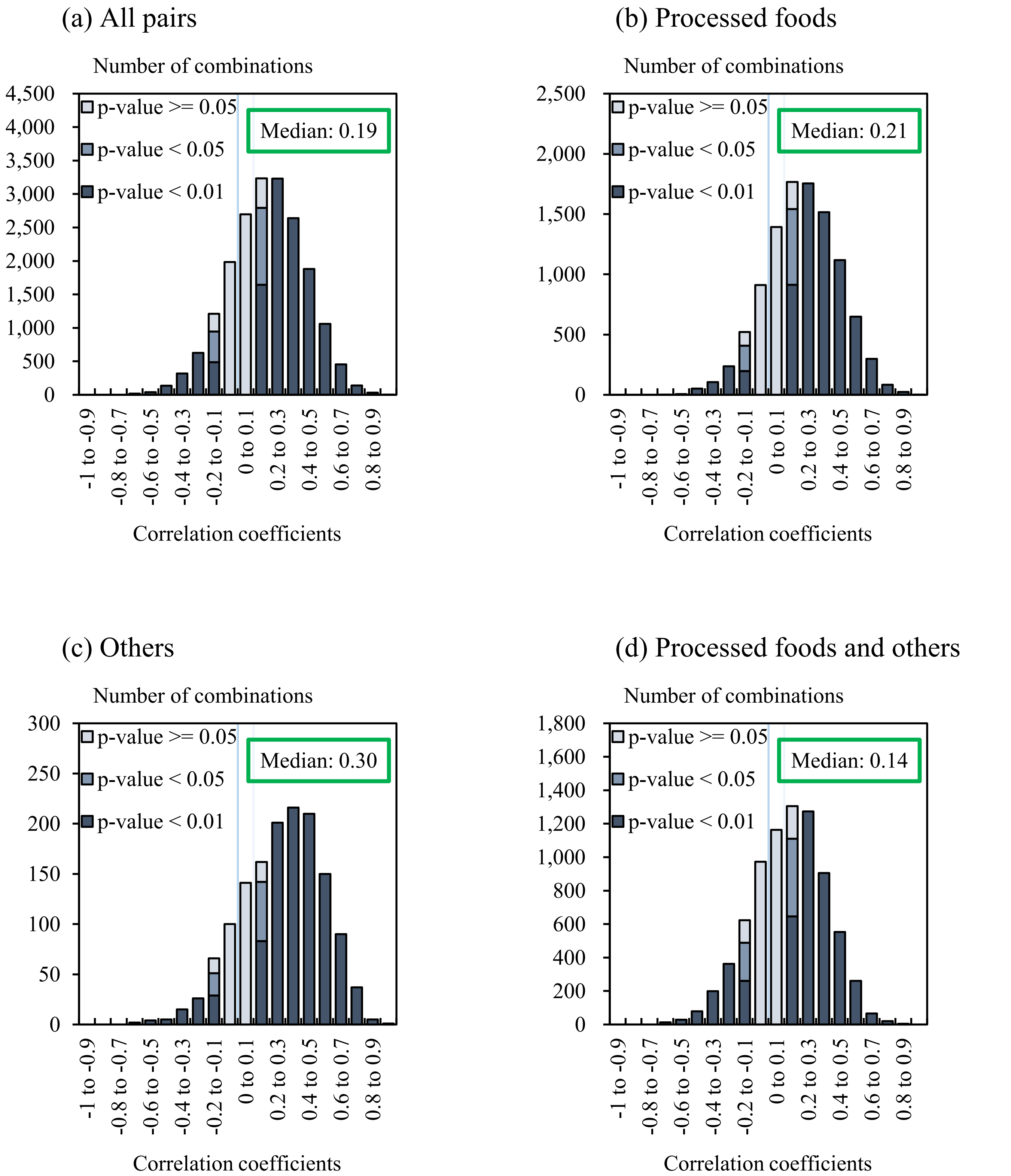
Notes: These panels show histograms of the correlation between the annual POS inflation rate and the standard deviation of the seasonal component of (a)the frequency of price increases, (b)the frequency of price decreases, (c)the size of price increases, and (d)the size of price decreases during the year, respectively, for all 199 categories. The data coverage is 1990 to 2021, excluding 2003 and 2004. The seasonal components are extracted by normalizing with the annual value.

Figure C3: Seasonality of Net Frequency and Net Size of Price Changes Extracted by Normalizing with the Annual Value



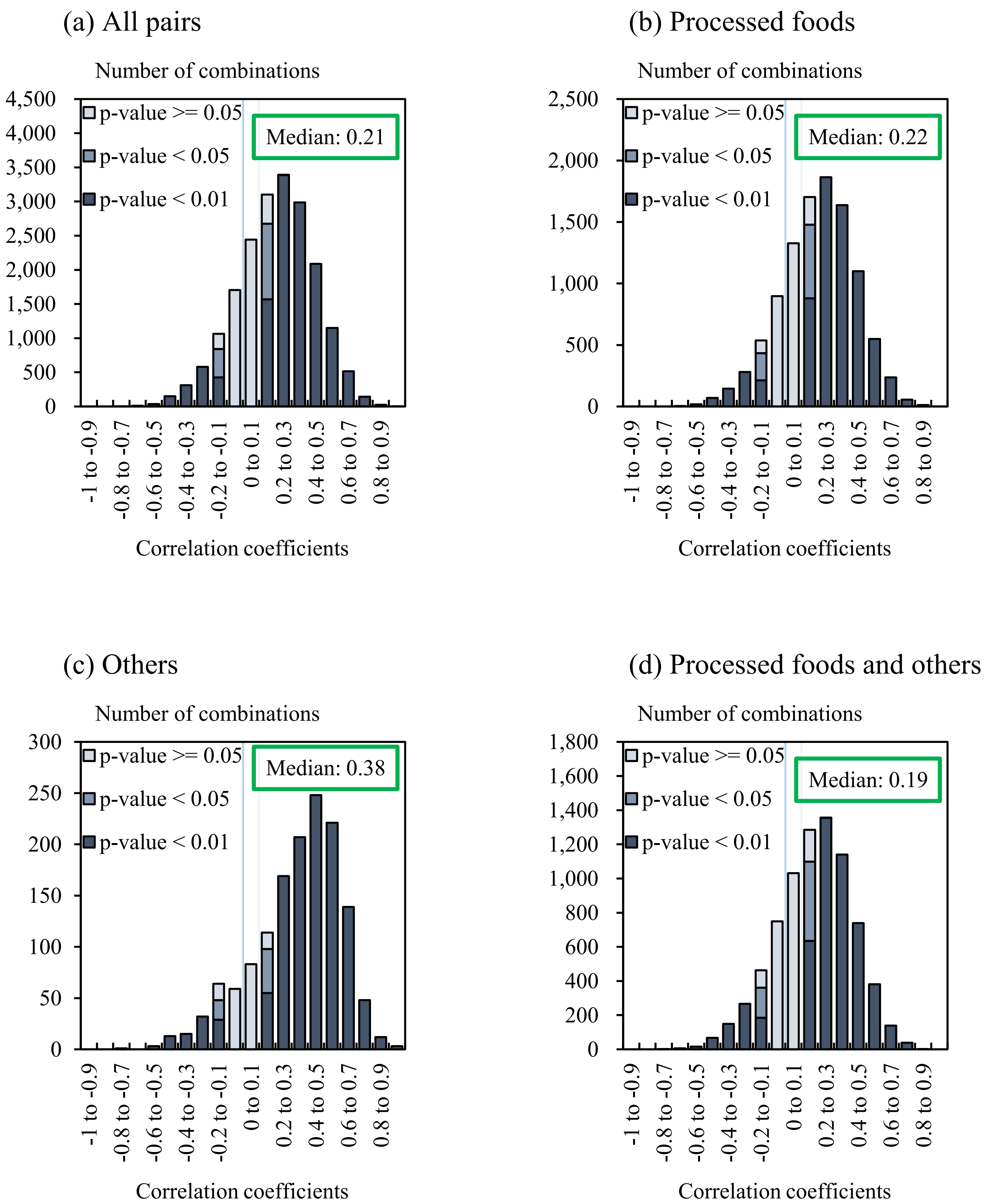
Notes: The panels plot the median of the average seasonal component of net frequency and net size of price changes across all categories. The shaded area indicates the 25th and 75th percentile bands. For extracting the seasonal components of net frequency, net size, and inflation rate, we subtract the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

Figure D1: Correlation of Frequency of Price Increases across Foods and Others



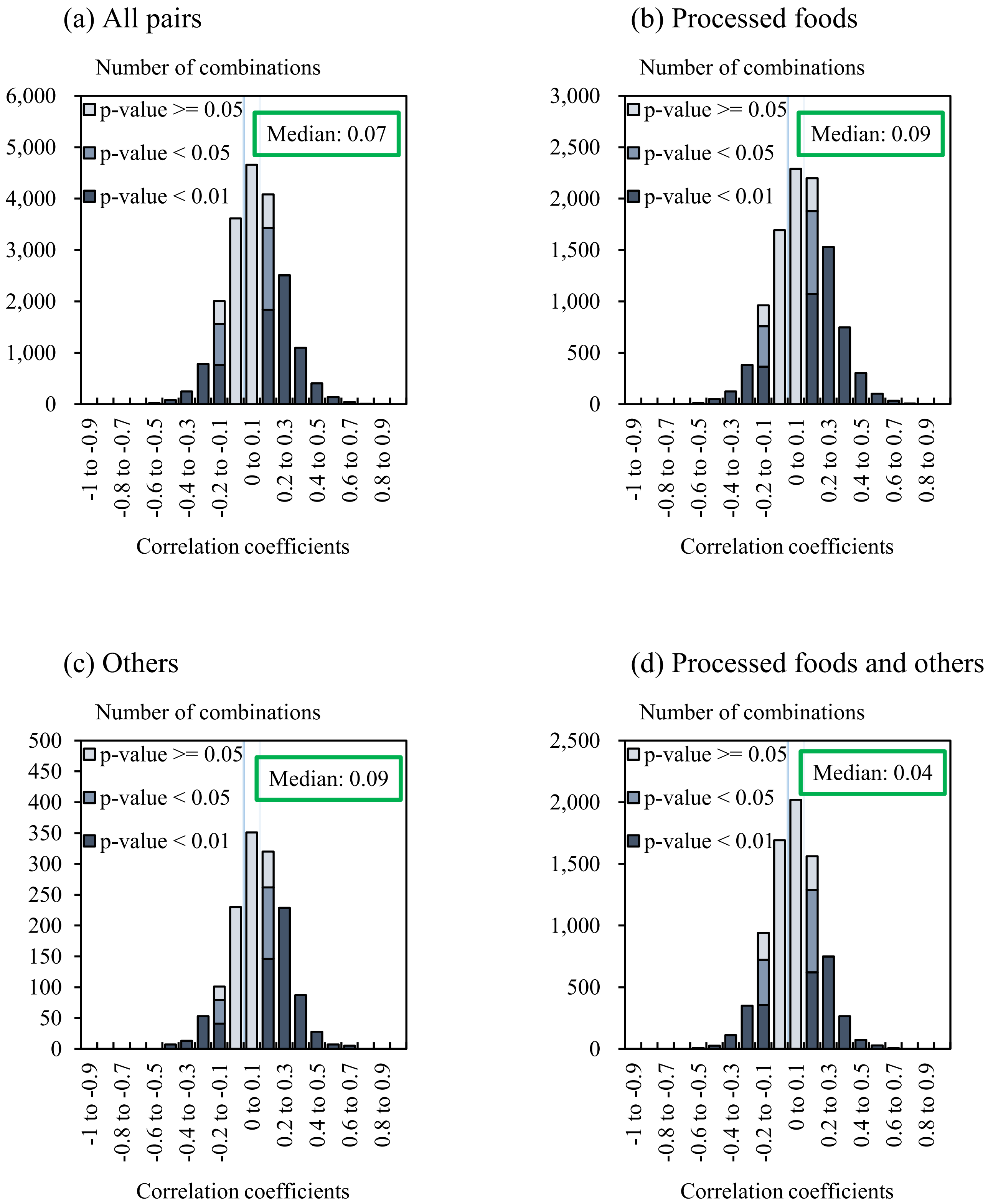
Notes: The panels show histograms of the correlations of the seasonal components of frequency of price increases across pairs of (a)all categories, (b)categories of processed foods, and (c)categories of others, respectively. Panel (d) indicates the correlation between categories of processed foods and those of others. Processed foods include 145 categries and others include 54 categories. The data coverage is 1990 to 2021, excluding 2003 and 2004.

Figure D2: Correlation of Frequency of Price Decreases across Foods and Others



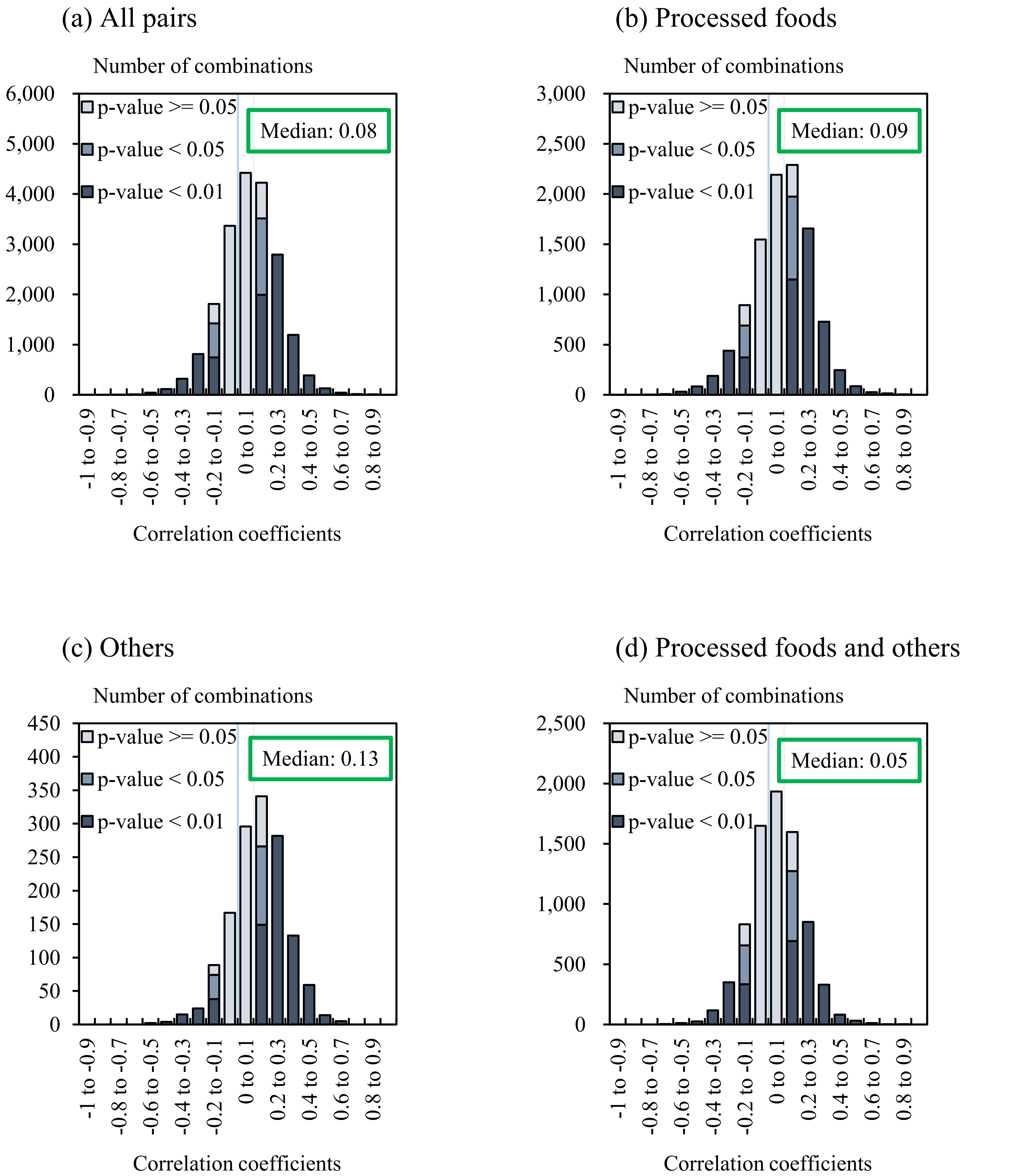
Notes: The panels show histograms of the correlations of the seasonal components of frequency of price decreases across pairs of (a)all categories, (b)categories of processed foods, and (c)categories of others, respectively. Panel (d) indicates the correlation between categories of processed foods and those of others. Processed foods include 145 categries and others include 54 categories. The data coverage is 1990 to 2021, excluding 2003 and 2004.

Figure D3: 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 categries and others include 54 categories. The data coverage is 1990 to 2021, excluding 2003 and 2004.

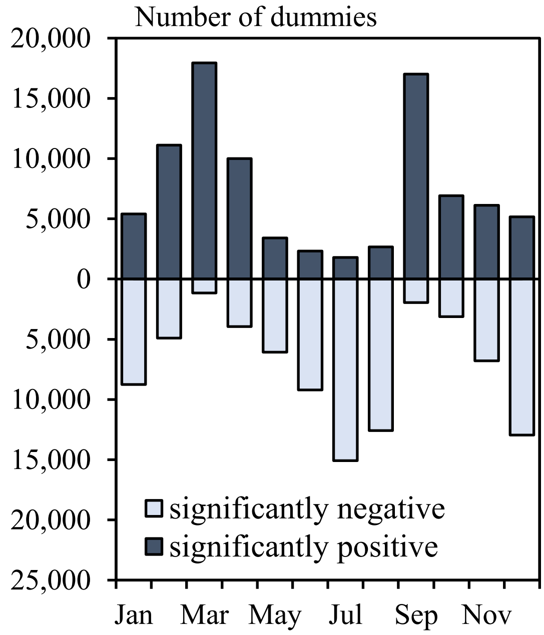
Figure D4: Correlation of Size of Price Decreases across Foods and Others



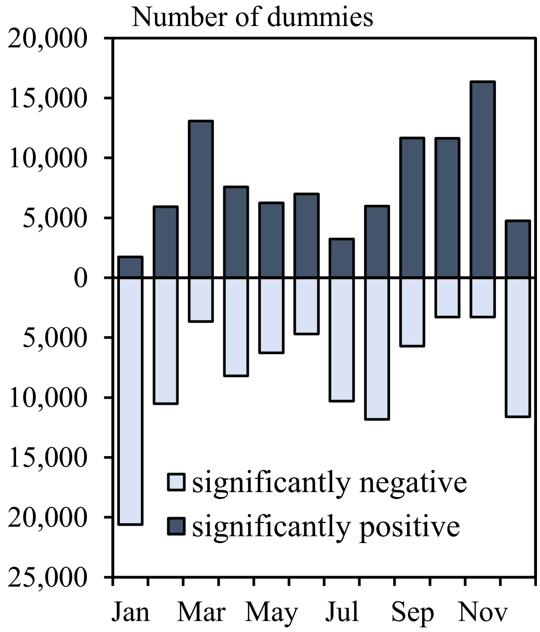
Notes: The panels show histograms of the correlations of the seasonal components of size of price decreases across pairs of (a)all categories, (b)categories of processed foods, and (c)categories of others, respectively. Panel (d) indicates the correlation between categories of processed foods and those of others. Processed foods include 145 categries and others include 54 categories. The data coverage is 1990 to 2021, excluding 2003 and 2004.

Figure E1: Number of Statistically Significant Monthly Dummies (1)

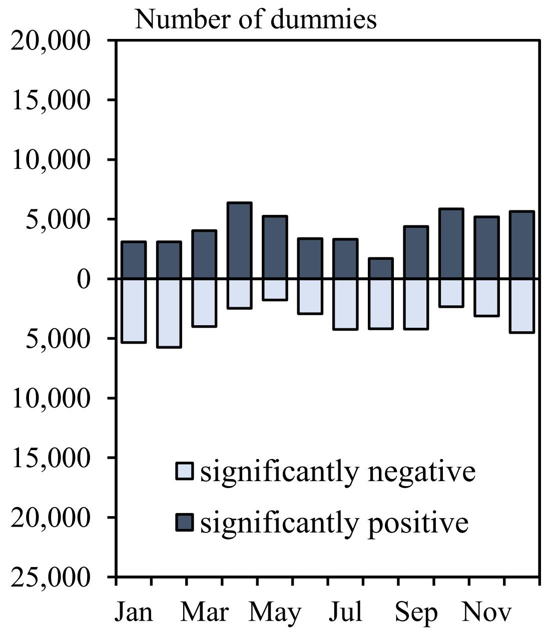
(a) Frequency of price increases



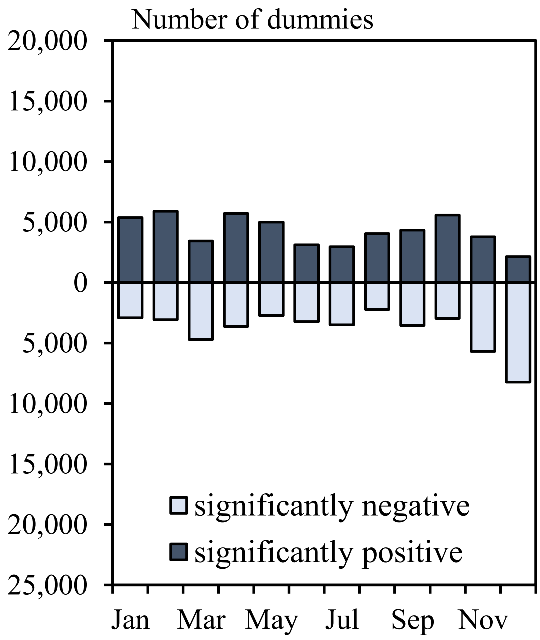
(b) Frequency of price decreases



(c) Size of price increases



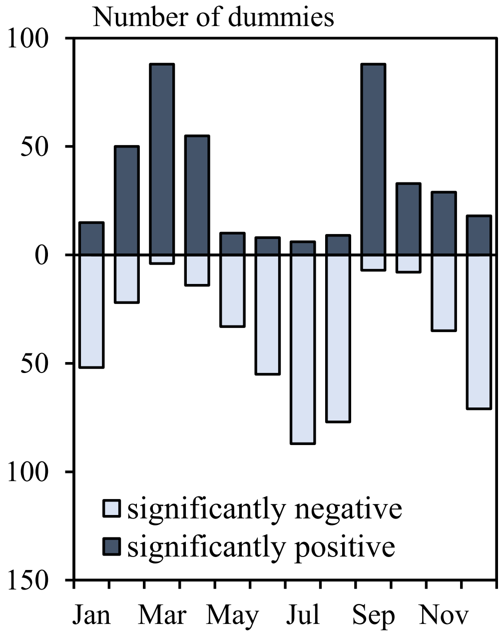
(d) Size of price decreases



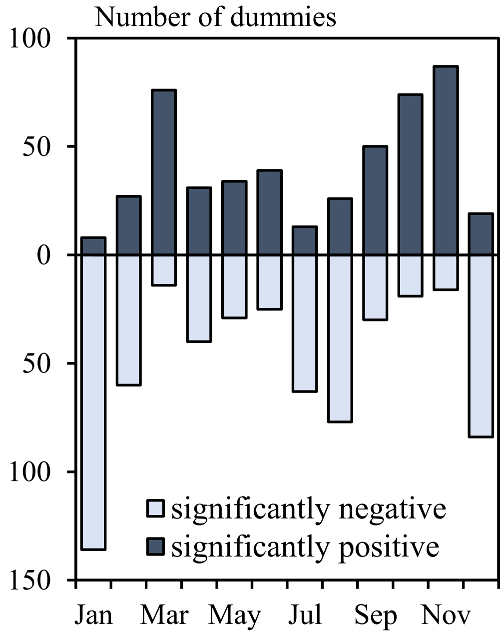
Notes: These panels show the number of statistically significant dummies in the estimation of equation (4). Dummies are estimated using a three-year rolling estimation for each of the 199 categories. For each category, there are about 300 coefficients on the dummies and overall there are 57,362. The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

Figure E2: Number of Statistically Significant Monthly Dummies (2)

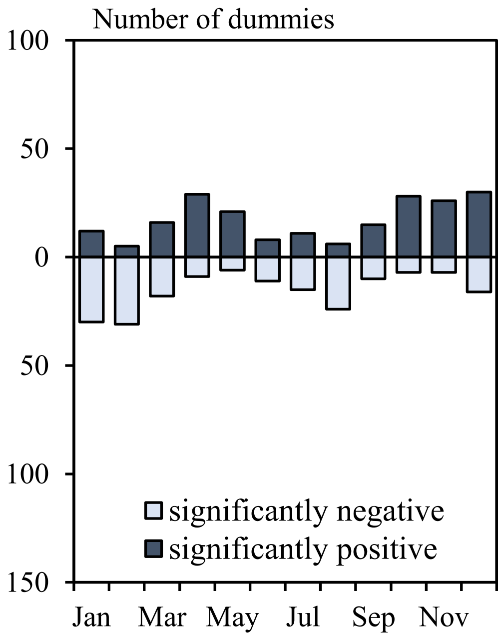
(a) Frequency of price increases



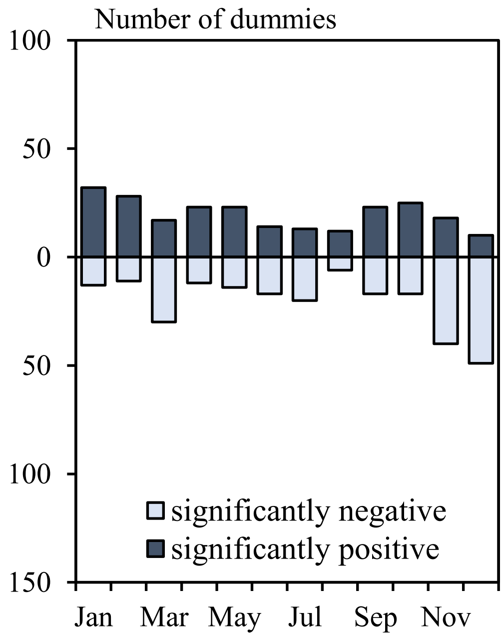
(b) Frequency of price decreases



(c) Size of price increases



(d) Size of price decreases



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% level is reported.