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Abstract

Using microdata from the Retail Price Survey (the basic statistics for the Consumer Price Index), we document facts regarding price stickiness in Japan. The main results are as follows: (1) The average frequency of price changes approximates 20% on a monthly basis. (2) The frequency of price changes is more heterogenous than that in the U.S. (3) Whereas no clear relationship exists between the frequency and size of price changes, a positive correlation emerges between the size of price changes and price dispersion across stores. (4) Large cities tend to have a higher frequency of price changes and smaller price dispersion than small cities. (5) A positive relationship exists between price changes and jobs-to-applicants ratio for some services, whereas a negative relationship exists between the frequency of price changes and jobs-to-applicants ratio for some goods. (6) Behind the 2022–23 price increase, the frequency of price changes exhibits a notable increase for certain goods and services such as eating out, while no distinct change is observed for the size of price changes or price dispersion.

JEL Classification Number: C33, E31, E52
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1 Introduction

Price stickiness stands as a pivotal determinant influencing the effectiveness of monetary policy. Despite an accretion of empirical studies on the extent of price stickiness, including in Japan, the accuracy of measuring price stickiness is impeded by constraints in data accessibility. Prevailing data are normally based on prices aggregated at the regional level, and although scanner data are frequently used nowadays, they are restricted exclusively to goods with services being frequently omitted. This problem is particularly serious in Japan.

The first objective of this study is to present facts on price stickiness in Japan by employing the rich micro-level Retail Price Survey (RPS) data, which is the basic statistics of the consumer price index (CPI). Specifically, the frequency of price changes is our focus, because it serves as the basis of macroeconomic models that assume price stickiness such as New Keynesian models, and thus, offering comprehensive tables at both the item and category levels is vital for calibrating model parameters in future research.[1]

The second objective is to analyze the relationships among various variables related to price stickiness, such as the frequency and size of price changes and cross-sectional dispersion in prices. This investigation holds significance in shaping a comprehensive model of price stickiness beyond the analysis of Japanese data. It will guide us in assessing the validity of sticky price models—such as menu cost and Calvo-type models—and in answering questions regarding whether aggregate or idiosyncratic shocks influence economic fluctuations and what causes heterogeneity in price stickiness. We leverage disparities across regions to empirically analyze whether these price stickiness variables are related to regional economic conditions, particularly, the effective jobs-to-applicants ratio. This estimation mirrors that of the Phillips curve with region, item, and month dummies in the fixed effects, while controlling for macroeconomic factors such as changes in inflation expectations and monetary policy.

It should be noted that our analysis is confined to Japan with no guarantee that the evidence of price stickiness is seamlessly extrapolated to other nations. Notably, Japan's prolonged period of comparatively subdued inflation rates may imply significant dissimilarities with other countries in the attributes of price stickiness. To probe inter-country differences, this study compares the frequency of price changes for items ubiquitously featured in the CPI in both Japan and the U.S.

[1] A csv file and tables are provided on the author's website and in the Online Appendix.

The main results obtained from the analysis are as follows: First, the average frequency of price changes (weighted average based on CPI weight) is 22% on a monthly basis. This metric varies widely across items with a standard deviation of 28%. The unweighted average and median are 25% and 16%, respectively, with values varying considerably depending on the aggregation method. The frequency of price changes tends to be lower for services than goods, and a polarization exists between items with highly flexible prices (especially fresh food) and items with prices rarely revised (especially services). The average size of price changes is 15%, and the cross-sectional price dispersion across stores is 26% and 32% in terms of standard deviation and the difference between the 75th and 25th percentiles, respectively.

Second, the frequency and size of price changes depend on the measurement method. Changes in field agents and specification (attributes of the surveyed goods) increase the measured frequency of price changes for particular services, including eating out and those related to domestic duties (e.g., automotive maintenance, barber services, and external wall coating). Conversely, the impact on goods is smaller. As services have a lower frequency of price changes than goods, the frequency of changes in field agents and specification cannot be neglected. Furthermore, the impact of regional aggregation is large. When the frequency of price changes is measured based on the prices aggregated at the municipal level to be the same as the published RPS, the frequency of price changes becomes considerably larger.

Third, a comparison of the frequency of price changes between Japan and the U.S. reveals that the variation in the frequency of price changes by item is greater in Japan than in the U.S. The frequency of price changes in Japan is higher than in the U.S. for items for which the frequency of price changes is commonly high in the two countries (especially fresh food), whereas the frequency of price changes in Japan is lower than in the U.S. for items for which the frequency of price changes is commonly low (especially services). In other words, the frequency of price changes is more heterogeneous in Japan. The macroeconomic implication of this fact is that because the sector with sticky prices has a persistently larger effect on aggregate price rigidity than that with flexible prices, when other conditions are equal, the effect of monetary policy on the real side of the economy is greater in Japan than in the U.S. (see Carvalho 2006).

Fourth, in examining the relationship among several variables related to price stickiness, we observe no clear relationship between the frequency and size of price changes, while a positive correlation is observed between the size of price changes and price dispersion across stores. At the item level, price dispersion tends to increase for items with larger price changes. Furthermore, the regression of the size of price changes on price dispersion as well as the fixed effects for each prefecture, item, and month reveals a significant positive relationship between the size of price changes and price dispersion. These results suggest that idiosyncratic shocks are more important than aggregate shocks in firms' price setting.

Fifth, an examination of heterogeneity by region suggests that the law of one price is not generally established for either goods or services. Specifically, price levels tend to be higher in larger cities for the categories of foods, services related to domestic duties, and services related to communication, culture, and recreation. However, there are some goods and services, such as other industrial products and eating out, for which there is no significant difference between large and small cities. Additionally, we find that larger cities tend to have a higher frequency of price changes. Finally, price dispersion from the national average for goods tends to be smaller in large cities than small cities. Large cities have higher population densities and shorter shopping distances between competing stores, which may result in smaller price differences.

Sixth, we examine the relationship between several price stickiness variables and employment conditions at the local level and find significant relationships for some services. We run the regression using price stickiness variables by prefecture, item, and month as the dependent variable, while the explanatory variables comprise the effective jobs-to-applicants ratio by prefecture and month and the fixed effects of prefecture, item, and month. When the log price difference (i.e., inflation rate) is used as the dependent variable, the coefficient on the effective jobs-to-applicants ratio is not significant for goods but is significant for some services (particularly, domestic duties and medical care and welfare). This result is consistent with the prediction by Hazell et al. (2022) that prices of tradable goods do not respond to region-specific factors, whereas those of non-tradable goods (i.e., services) do. However, when the frequency of price changes and price dispersion are used as the dependent variable, the coefficient on the effective jobs-to-applicants ratio is no longer significant for services, while the coefficient is significantly negative and positive, respectively, for goods. In other words, the stronger the job offers, the lower the frequency of price changes and the greater the price dispersion. A possible explanation for this is that when job offers are strong, households are busy working and have less time to shop (higher opportunity cost of shopping), which reduces demand elasticity; thereby, retailers do not change prices frequently and price dispersion increases across stores.

Seventh, we assess the frequency and size of price changes and price dispersion during the 2022–23 price-increase phase. We find no clear change in the size of price changes or price dispersion, but an increase in the frequency of price changes for certain goods and services including eating out. This suggests that a state-dependent sticky price model fits the data better than a time-dependent sticky price model.

Numerous studies measure price stickiness both overseas and in Japan.[2] Of these, Higo and Saita's (2007) study is most relevant to our study. The most notable difference is that Higo and Saita (2007), as well as Ikeda and Nishioka (2007) and Kaihatsu, Katagiri, and Shiraki (2023), use published aggregated data from the RPS. As these studies' authors acknowledge, the frequency of price changes is overestimated because a price change in any store among several stores in a region is considered a price change when we use the aggregated RPS data. Abe and Tonogi (2010) and Sudo, Ueda, and Watanabe (2014) use supermarket scanner data to analyze price stickiness. Unlike the RPS and CPI, which cover only representative items, the scanner data cover all goods provided they are sold in supermarkets. However, the scanner data do not include items that are not sold in supermarkets—notably, services such as eating out and cutting hair. The contribution of this study to the existing body of research on the U.S. and Europe is constrained, primarily owing to the long-standing availability of similar data in these regions. Nonetheless, our study adds value by shedding light on price dispersion, which has received comparatively less attention in prior research, and delving into a more detailed examination of regional heterogeneity.

In recent years, there has been a notable surge in the body of research focused on price dynamics while considering regional heterogeneity (e.g., Nishizaki and Watanabe 2000, Fitzgerald and Nicolini 2014, McLeay and Tenreyro 2019, Hazell et al. 2022, and Kishaba and Okuda 2023). One challenge in analyzing the determinants of price setting, especially the effect of economic activity, is that aggregate shocks, such as monetary policy and technology shocks, affect not only economic activity but also inflation expectations. This issue becomes particularly pronounced during periods of declining inflation expectations, as witnessed during the Great Moderation, which may make the estima-

[2]Examples are Bils and Klenow (2004), Klenow and Kryvtsov (2008), and Nakamura and Steinsson (2008) for the U.S.; Dhyne et al. (2006) and Gautier et al. (2023) for Europe; and Higo and Saita (2007), Ikeda and Nishioka (2007), Abe and Tonogi (2010), Sudo, Ueda, and Watanabe (2014), and Kaihatsu, Katagiri, and Shiraki (2023) for Japan.

tion of the slope of the Phillips curve seriously biased unless inflation expectations are appropriately controlled. To address this challenge, regional data can be used to analyze the effects of region-specific economic activity on price dynamics in a particular region, while controlling aggregate factors. Hazell et al. (2022) construct a sticky price model comprising tradable and non-tradable goods (equivalent to services) and two regions and demonstrate that the slope of the Phillips curve for an entire country can be estimated from the Phillips curve for non-tradable goods using panel data and the time fixed effects. Kishaba and Okuda (2023) apply the framework by Hazell et al. (2022) to the Japanese data. A distinguishing feature of our analysis—compared with that of Hazell et al. (2022) and Kishaba and Okuda (2023)—is our breakdown of prices, considering both the frequency and size of price changes. However, in contrast to Kishaba and Okuda (2023), our study is constrained by limitations in accessing microdata, resulting in a shorter data period restricted to the period after 2012. This timeframe corresponds to a period characterized by low inflation and nearly zero nominal interest rates, commonly associated with a flat Phillips curve.

The structure of this paper is organized as follows. Section 2 provides an overview of the RPS data and variable definitions. Section 3 presents the results of price stickiness, such as the frequency and size of price changes and price dispersion. Section 4 presents the results for the relationship between the variables related to sticky prices. Section 5 presents the results for regional heterogeneity. Section 6 presents the results for the estimation of the Phillips curve. Section 7 examines time-series changes in the frequency and size of price changes and price dispersion. Section 8 concludes.

2 Overview of the RPS Data and Definition of Variables

2.1 Retail Price Survey

The RPS is one of the fundamental statistics based on the Statistics Act in Japan, which forms an integral component of the CPI. The RPS involves a survey conducted by field agents who gather price data from as many as 576 retail stores spanning the entire nation. See the Online Appendix for the descriptive statistics such as surveyed items, weights in terms of expenditure (CPI weights), and the number of surveyed shops.

For this study, we obtain microdata on the RPS, which include prices by stores on a monthly basis. This allows us to analyze price stickiness in detail, particularly ensuring accurate calculation of the frequency and size of price changes and price dispersion.

Several items are excluded from our analysis. Some items are not surveyed in the RPS because (1) they do not have a defined survey area (e.g., gasoline and waterworks), (2) they have uniform prices nationwide or regionally (e.g., electricity, communication charges, and railroad fares), or (3) prices are collected using web scraping or POS data (e.g., personal computers, airfare, and accommodation). In addition, (4) rent is excluded from our analysis because it requires separate handling, and (5) items that are surveyed in the RPS but not in the CPI are also excluded. Some items are surveyed three times in a month because of their extreme price volatility (e.g., cabbage), which we do not analyze in some cases.

Our analysis covers 511 items, and the expenditure weight of these items (CPI weight, 2020 base) compared with the overall CPI items (582 items, 2020 base) is approximately 60%. Notably, rent constitutes a significant portion of the excluded items, contributing to about 20% of the overall CPI weight. It is worth highlighting that rent, particularly imputed rent, is widely recognized for its remarkable price rigidity. Conversely, the excluded items like personal computers and airfare, which rely on web scraping and POS data, exhibits a tendency towards frequent price changes.

The data period begins in September 2012, owing to limitations in the availability of micro RPS data. Data on prefectural survey items (so-called D items, e.g., water and sewerage charges, college and university fees) are available only from October 2016. The data period ends in April 2023.

2.2 Definition of Variables

We focus primarily on the following variables.[3] The first variable is the price level. We calculate the unweighted average price across stores by item and month, where we ignore the records that are not surveyed—denoted by NAs (not available). We index the price level by standardizing September 2012 to one.

The second is the frequency of price changes, which we calculate in the following

[3] An important variable related to price stickiness that is not dealt with in this paper is the hazard probability (conditional probability of a price change after consecutive price unchanges), which is presented in the Online Appendix.

steps. First, we record whether a price is changed from the previous month for each item, month, and store. The conditions for determining price changes are that prices are surveyed both in the previous and current months; the price difference is at least two yen; no change occurs in field agents or item specification (attributes of surveyed goods); and the month is not April 2014 or October 2019, months observing the rise in the consumption tax rate. Data for NAs are ignored, though assuming that the price exhibits no change from the previous month is possible. Second, for each item and month, we calculate the fraction of stores wherein prices are revised and define this as the frequency of price changes. For the items that are surveyed three times in a month (early/mid/late period), we calculate the frequency of price changes from the previous period (i.e., around 10 days before), but not from the previous month. Denoting this as f, we calculate the monthly frequency of price changes as $1-(1-f)^3$.

The third is the size of price changes. It is calculated for each item and month by recording the absolute size of price changes when a price change is determined, dividing it by the previous month's price, and then taking the simple average.

The fourth is price dispersion across stores. After obtaining the logarithmic values for the price for each item, month, and store, we calculate price dispersion across stores as the standard deviation or difference between 75th and 25th percentiles.

Price dispersion—despite receiving less attention in existing studies than the frequency and size of price changes—is closely related to welfare losses in the New Keynesian model based on Calvo-type price stickiness. Price dispersion signals that labor is not efficiently supplied to sectors, and deviations from the law of one price can lower consumer surpluses (see Nakamura et al. 2018).

Our methodology encompasses the calculation of several key metrics for each item and month, including the price level, frequency of price changes, size of price changes, and price dispersion. In general, items in the RPS directly correspond to items in the CPI. However, in some cases, a more diverse set of items are surveyed in the RPS (especially the D items) than in the CPI.[4] In such cases, we calculate simple averages for the multiple items surveyed in the RPS that pertain to a specific CPI item.

[4]For example, consider the CPI item of college and university fees (national). In the RPS, various prices are surveyed, such as (1) national college and university tuition fees for the courses of law, literature, and economics, (2) national college and university tuition fees for the courses of science and technology, (3) national college and university entrance fees for the courses of law, literature, and economics, and (4) national college and university entrance fees for the courses of science and technology.

These variables calculated for each item are aggregated based on the CPI weights. We use two tiers of categories for aggregation following the CPI and Higo and Saita (2007). The first is a large category, consisting of the following five classifications: fresh food, goods (excluding fresh food), goods (public), services, and services (public). The other is a medium category, consisting of 19 classifications such as textiles and eating out. The categories not labeled *public* are those in the private sector. When averaging over time, we take simple averages.

3 Frequency and Size of Price Changes and Price Dispersion

3.1 Main Results

Table 1 summarizes the frequency and size of price changes and price dispersion for the items in RPS. The CPI-weighted mean of the frequency of price changes is 22% on a monthly basis. The unweighted mean and median are 25% and 16%, respectively. The standard deviation of the frequency of price changes is 28%, indicating high heterogeneity. Figure 1 depicts the histogram of the frequency of price changes by item, indicating that the frequency of price changes is broadly divided into the following two modes: highly flexible items with the frequency close to one and rigid items with the frequency close to zero. Items with a high weight tend to have a low frequency of price changes, making weighted mean smaller than unweighted mean.

The frequency of price changes is nearly the same as that in Higo and Saita (2007), which is 21%. Two points should be noted. First, Higo and Saita (2007) use the published RPS, wherein prices are aggregated. Using aggregated price data generates an upward bias in calculating the frequency of price changes. Second, the analysis period is different. Our data cover the period from 2012 to 2023, whereas Higo and Saita (2007) use data from 1999 to 2003. As the slope of the Phillips curve has reportedly flattened in recent years, the frequency of price changes in our data period may be lower than that in the period analyzed by Higo and Saita (2007).

The weighted mean of the size of price changes is 15%. The left-hand panel of Figure 2 illustrates a histogram of the size of price changes by item, which exhibits a single-mode distribution peaking around 15% and no clear differences by category.

Price dispersion is substantial. It is 26% and 32% in standard deviation and the difference between the 75th and 25th percentiles, respectively. As the RPS examines the prices of certain pre-specified items, this result suggests that the law of one price does not hold, with variations of approximately 30% from one store to another. The figure on the right-hand side of Figure 2 presents a histogram of price dispersion based on standard deviation by item, which does not exhibit bimodal patterns or any discernible dependence on item characteristics, unlike the pattern observed in the frequency of price changes.

Tables 2 and 3 summarize the frequency and size of price changes at the large and medium category levels, respectively. A comparison of the CPI weights of the items surveyed in the RPS and CPI indicates that, while the RPS covers almost all CPI items for fresh food, there are large omissions in services. Among services, zero or extremely low coverage is observed in rent; those related to communication, culture, and recreation; those related to domestic duties (public); and those related to culture and recreation (public).

Fresh food and petroleum products stand out with a remarkably high frequency of price changes, surpassing 50% on a monthly basis. In contrast, several categories, primarily within the service sectors, such as eating out and services related to domestic duties, exhibit a notably low frequency of around 1% or even less.

3.2 Dependence on Measurement Methods

We assess the extent to which measured price stickiness varies depending on the calculation method (Tables 4 and 5). In the CPI and RPS, surveyed items (item specifications) are reviewed every month, in addition to major revisions every five years. Furthermore, field agents occasionally change. While in the benchmark study, the frequency of price changes is calculated by excluding the month in which surveyed items or field agents are changed, we calculate the frequency of price changes by including (i.e., ignoring) these changes.

Table 4 summarizes the effects of changes in item specifications and field agents on the measurement of the frequency and size of price changes. The overall effects are modest. However, the frequency of price changes undergoes considerable changes for certain services— particularly, eating out and services related to domestic duties. When the frequency of price changes is calculated but changes in field agents are neglected, the value for eating out and services related to domestic duties increases from 2.2% to 3.2% and from 1.1% to 1.5%, respectively. This suggests the possibility that, for items with a low frequency of price changes, changes in field agents occur more frequently than actual price changes, resulting in an upward bias in the measurement of price changes if we ignore this effect. Another possibility is that item specifications for services are inherently more ambiguous compared to those for goods, which lead to a greater degree of discretion exercised by field agents when collecting price data. Furthermore, the table indicates that for services related to domestic duties, the effect of changes in item specifications on the measurement of the size of price changes is substantial. When we ignore this, the size of price changes increases from 15% to 45%.

Next, we examine the effects of regional aggregation on the measurement of the frequency of price changes. The RPS appears to publish prices as a simple average of prices in multiple stores within a municipality, rounding to the first decimal place. For this reason, in previous studies (Higo and Saita 2007, Ikeda and Nishioka 2007, and Kaihatsu, Katagiri, and Shiraki 2023) that examine price stickiness using published RPS data, the frequency of price changes is measured as if it were one, even when only one store in a municipality revises its price while other stores maintain their prices unchanged (i.e., an upward bias in the frequency of price changes). Moreover, the RPS does not publish prices for all cities (e.g., in Hokkaido prefecture, the published RPS comprises three regions, while the micro RPS data include six regions).

To validate this potential upward bias, we calculate the frequency of price changes after aggregating prices within the same region (city, town, village level, or prefecture level) for the eating-out category. Table 5 clearly demonstrates that, as anticipated, the greater the degree of aggregation (baseline → city, town, village → prefecture), the higher the reported frequency of price changes. For example, for udon (Japanese noodle), the original frequency of price changes stands at 2.6%, but this increases considerably to 6.4% when aggregated by city, town, or village, and further escalates to 14.9% when aggregated by prefecture. These findings underscore the substantial impact of aggregation on the measurement of the frequency of price changes and emphasize the importance of utilizing micro RPS data for more precise analysis.

3.3 Comparison between Japan and the U.S.

We compare the frequency of price changes between Japan and the U.S, utilizing data from the table provided in the appendix by Bils and Klenow (2004) and focusing on items that are commonly surveyed in both countries. However, it is important to note that there are significant differences in the composition of items within certain categories between the two countries. For example, in Japan, the eating-out category comprises a wide variety of food items such as udon, Chinese noodles, spaghetti, and hamburgers, while in the U.S., it is classified more broadly as lunch or dinner. Similarly, in the category of fresh food, Japan offers a diverse range of seafood items such as tuna, sardines, and salmon, while the U.S. offers only fish excluding canned. By contrast, the U.S. has a broader array of repair supplies and infant clothing items. For details, see the table in the Online Appendix. The fraction of items common in both countries is 61% and 47% in Japan and the U.S., respectively (calculated as the number of common items divided by the number of items for Japan or the U.S.). Based on the CPI weight, the fraction of common items is 68% in Japan and 46% in the U.S. Another important note is that price changes owing to temporary sales are included in the U.S. Bils and Klenow (2004) document that temporary sales make up approximately 20% of price changes, whereas Nakamura and Steinsson (2008) argue that the effect of temporary sales is larger, accounting for about 50% of price changes.

Figure 3 depicts a scatter plot of the frequency of price changes for common items with Japan on the horizontal axis and the U.S. on the vertical axis. The following observations are made: First, items with a high frequency of price changes in Japan tend to have a high frequency of price changes in the U.S. as well (i.e., positive correlation). Second, for items for which the frequency of price changes is high in both Japan and the U.S. (especially fresh food), the frequency of price changes is even higher in Japan than in the U.S. Third, contrary to the second result, for items for which the frequency of price changes is low in the two countries (especially services), the frequency of price changes is lower in Japan than in the U.S. The second and third results suggest a flatter slope of the regression line, with the estimated slope being 0.42 (significant at the 5% level). Furthermore, the data reveals that the standard deviation in the frequency of price changes across items is about twice as large for Japan at 0.32 (or 32%) compared to 0.17 for the U.S, whereas the average frequency of price changes is comparable (0.28 for Japan and 0.27 for the U.S.) Although the inclusion of temporary sales increases the frequency of price changes for the U.S., this is predominantly exclusive for goods, and the result that the frequency of price changes in the U.S. is higher than that in Japan remains valid for the category of services.

This result suggests that overall price stickiness as a determinant of the real effect of monetary policy is more pronounced in Japan than in the U.S. Carvalho (2006) shows that when price stickiness is heterogeneous, overall price stickiness is greater than when it is homogeneous, and the real effect of monetary policy is larger. This is because when monetary policy shocks occur, the share of sectors with rigid prices becomes relatively prominent among firms that did not adjust their prices, which Carvalho (2006) calls the frequency composition effect. Furthermore, Aoki (2001) suggests that an optimal monetary policy should refer to price changes in sectors with rigid prices, and in this respect, placing greater emphasis on service sectors is desirable in Japan than in the U.S., as these sectors tend to exhibit lower frequency of price changes and greater price stickiness.

4 Relationship between Price Stickiness Indicators

This section presents an examination of the relationship between the three main indicators of price stickiness: the frequency of price changes, the size of price changes, and price dispersion.

Before presenting the empirical results, we consider the theoretical relationship between the frequency and size of price changes. When aggregate shocks dominate idiosyncratic shocks, we might expect a negative correlation between the frequency and size of price changes. For example, in the Calvo-type sticky price model, where firms have a fixed probability of adjusting their prices each period, the size of price changes will be smaller the higher the frequency of price changes. Similarly, in a state-dependent sticky price model, where menu costs vary across items, smaller menu costs lead to a higher frequency of price changes and smaller price adjustments.

On the contrary, there is a plausible scenario that the frequency of price changes is positively correlated with the size of price changes. In particular, when menu costs are uniform across items and idiosyncratic shocks exert a dominant influence, both the frequency and size of price changes will be larger for items with greater idiosyncratic shocks.

When menu costs are heterogeneous and idiosyncratic shocks dominate aggregate shocks, the frequency of price changes is likely to be uncorrelated with the size of price changes. The idiosyncratic nature of shocks and the variability in menu costs across firms can result in diverse responses to price adjustments. A similar expectation holds in the Calvo-type model. Specifically, when idiosyncratic shocks dominate over aggregate shocks, the frequency of price changes is expected to be uncorrelated with the size of price changes.

Figure 4 depicts scatter plots of the frequency and size of price changes for each item or medium category, which shows an insignificant correlation. Columns (1) and (2) of Table 6 confirm this result: the estimation result shows no significant relationship between the two variables, suggesting the dominance of idiosyncratic shocks over aggregate shocks.

While the above analysis is based on time and regional average of the frequency and size of price changes, it is possible to break down the variables by prefecture and month. We conduct a regression of the panel data, wherein the dependent variable is the size of price changes and the explanatory variables are the frequency of price changes and the fixed effects for prefectures, items, and months.

Table 7 presents the estimation results, indicating a significant positive relationship between the frequency and size of price changes for the service category. This can be explained when idiosyncratic shocks dominate and the size of menu costs hardly vary across items. A barely significant positive relationship at the 10% level is observed for goods excluding fresh food, whereas no significant relationship is observed for fresh food and services (public).

Next, we focus on price dispersion among stores and analyze its relationship with the frequency and size of price changes. Figure 5 is a scatter plot of the size of price changes and price dispersion based on standard deviation for each item or medium category. Unlike Figure 4, a significant positive correlation is observed between the two variables. By contrast, although not presented in the figure, no clear relationship is observed between the frequency of price changes and price dispersion.

Columns (3) to (8) in Table 6 present estimates with price dispersion as the dependent variable and the frequency and size of price changes as the explanatory variables. The coefficient on the size of price changes is almost consistently positive and significant. In the right-hand side panel of Figure 5, the point on the lower right is services related to medical care and welfare (public), where prices are, to a large extent, determined by the government. With this exclusion, the correlation coefficient is significant (Columns (6) and (7)). By contrast, the coefficient on the frequency of price changes is significantly positive in Columns (3) and (4), but not significant in Columns (5) to (8), implying no robust relationship between the frequency of price changes and price dispersion.

Like the analysis in Table 7, we run a regression with price dispersion as the dependent variable and the frequency and size of price changes as the explanatory variables, with the fixed effects for prefectures, items, and months included. Table 8 indicates a significant positive relationship between the size of price changes and price dispersion for all large categories. In other words, price dispersion tends to increase for items for which the size of price changes increases. By contrast, the coefficient on the frequency of price changes is significantly negative in the three large categories except for fresh food (only at the 10% level for services). In other words, price dispersion tends to decrease for items with the increased frequency of price changes. We decompose the frequency of price changes into the upward and downward frequency of price changes, and the estimation results show that the absolute value of the coefficient is larger for the upward frequency of price changes than for the downward frequency of price changes. Thus, price dispersion is more responsive to the upward frequency of price changes than to the downward frequency of price changes.

In summary, we find an insignificant or positive relationship between the frequency and size of price changes as well as a positive relationship between the size of price changes and price dispersion. Can these results be explained by the dominance of idiosyncratic shocks? The answer is probably yes. For items with large idiosyncratic shocks, the Ss band (the price inaction range) widens based on the menu cost model, resulting in large price dispersion. Large idiosyncratic shocks also increase the size of price changes, which generates a positive relationship between the size of price changes and price dispersion. However, explaining the negative relationship between the frequency of price changes and price dispersion, as observed in Table 8, may pose challenges.

5 Regional Heterogeneity

In this and subsequent sections, we analyze price stickiness by utilizing detailed information regarding regions provided in the RPS.[5] In this section, we analyze the relationship between price stickiness and the size of economic activity in cities. We address the fol-

[5] In the U.S., CPI prices are surveyed monthly only in Chicago, Los Angeles, and New York. In other regions, prices are surveyed every two months, except those for food and energy, which limits the regional variations in the analysis of price stickiness (see Nakamura and Steinsson 2008).

lowing questions: Do large cities have a greater frequency of price changes and earlier timing of price changes? We run the following regressions:

$$y_{is} = \alpha_i + b \cdot \log(\text{city weight}_r) + \varepsilon_{is}, \tag{1}$$

where i, s, r represent an item, shop, and municipality in which shop s is located. The dependent variable y_{is} is several indicators of price stickiness, whereas the explanatory variable city weight$_r$ is the size of economic activity of municipality r given by the CPI weights in the base year 2015.[6]

The estimation results are presented in Tables 9 to 12, in which the dependent variables are the logarithm of prices, frequency of price changes, size of price changes, and price dispersion. The logarithm of prices is used to examine whether the law of one price holds across cities. Price dispersion is defined as the absolute difference between the logarithm of the price in the shop and national average.

Table 9 shows that for price levels, the higher the price, the larger the city for several product categories (fresh food, food products, services related to domestic duties, and services related to communication, culture, and recreation). This suggests that the law of one price does not hold for not only services (non-tradable) but also several goods (relatively more tradable). However, no significant price difference is observed for other product categories (textiles, other industrial products, eating out, and services related to education).

Table 10 reveals that when the dependent variable is the frequency of price changes, the coefficients are significantly positive for almost all product categories. This suggests that the larger the city size, the higher the frequency of price changes. According to Table 11, the signs of the coefficients are mixed for the size of price changes. The coefficients are significantly positive for fresh food, textiles, eating out, and services related to forwarding and communication (public), while they are negative for food products. Table 12 shows that for the goods in textiles and other industrial products, the coefficients are significantly negative, indicating that the larger the city size, the smaller price dispersion. One plausible explanation of this result is that as city size grows, it typically corresponds to higher population density and a reduction in the size of the shopping or competitive marketplace. This brings the pricing environment closer

[6] In the CPI, weights are calculated from the product of the amount spent per household and the number of non-agricultural, forestry, and fishing households. We do not consider the area of municipalities. See https://www.stat.go.jp/data/cpi/2015/kaisetsu/pdf/0.pdf.

to adhering to the principles of the law of one price.

The subsequent question is whether price changes occur earlier in large cities such as Tokyo compared to small cities, with prices spilling over from Tokyo to rural areas. To address this question, first, we calculate the fraction of price changes by month, item, and region. Regions are categorized into large and small cities, with a specific focus on a small city referred to as "small city A" based on the RPS. Furthermore, we select the metropolitan area of Tokyo consisting of the 23 Tokyo wards and the three major large cities surrounding Tokyo (Saitama, Yokohama, and Chiba). Second, for each item, we calculate correlation coefficients for pairs of large and small cities or for pairs of Tokyo wards and cities surrounding Tokyo. To capture potential lead-lag relationship, we calculate correlation coefficients with a one-month shift applied to each pair.

Figure 6 depicts the scatter plot. Each point represents the correlation coefficient for each item, for pairs of large and small cities on the left and for pairs of Tokyo wards and cities surrounding Tokyo on the right. The horizontal axis represents the correlation coefficient when large cities or Tokyo are one month ahead, while the vertical axis represents that large cities or Tokyo are one month behind. If price changes occur earlier in large cities and Tokyo than in small cities and cities surrounding Tokyo, there should be more points to the lower right of the 45-degree line. The figure shows that despite a positive correlation, neither a clear leading nor lagging effect is observed between the regions. The absence of a clear leading or lagging effect implies that the timing of price changes does not exhibit a consistent and systematic pattern where large cities influence smaller cities or regions with a predictable time delay.

6 Estimating the Phillips Curve

Following the previous section, we analyze the relationship between economic activity and prices using regional variations. Specifically, we focus on the cyclical aspects of inflation dynamics to estimate the Phillips curve, that is, the relationship between real and nominal variables. Following Hazell et al. (2022) for the U.S. and Kishaba and Okuda (2023) for Japan, we run the following regression:

$$y_{ipm} = \alpha_i + \alpha_p + \alpha_m + b \cdot \text{job}_{pm} + \varepsilon_{ipm}, \tag{2}$$

where y_{ipm} represents the price variable for item i, prefecture p, and month m, and job_{pm} represents the effective jobs-to-applicants ratio obtained from Ministry of Health, Labour and Welfare.[7] Coefficient b represents the slope of the Phillips curve, indicating the extent to which changes in real economic activity impact the inflation rate. While endogeneity is generally a challenge in estimating the Phillips curve, the advantage of this estimation is that by utilizing regional and time variations and including their fixed effects, we can control for the channel, wherein aggregate shocks affect prices through inflation expectations.

The contribution of this analysis, compared to that of Hazell et al. (2022) and Kishaba and Okuda (2023), is that we analyze not only price change (inflation rate) but also the component of that change using the RPS microdata. Specifically, the frequency and size of price changes and price dispersion can be used as the dependent variable. As previously mentioned, in the U.S. CPI, prices are surveyed every other month in many cities except for food and energy, making this type of analysis particularly difficult for services.

According to the model developed by Hazell et al. (2022), the coefficient obtained by estimating the price change of services is the same as the slope of the Phillips curve for an entire economy. The coefficient for goods, which are predominantly tradable, is predicted to be insignificant because of the law of one price.

Table 13 presents the estimation results when the dependent variable is price change (i.e., log month-to-month difference in price times 100). The coefficient on the effective jobs-to-applicants ratio is positive at 0.08 for the large category of services though it is not significant at the 5% level (but significant at the 10% level). The size of the coefficient indicates that a one-unit increase in the effective jobs-to-applicants ratio increases the inflation rate for services by 0.08%, which is similar to Kishaba and Okuda's (2023) result—that is, approximately 0.1. Table 14 summarizes the coefficient on the effective jobs-to-applicants ratio for each medium category. Among private services, the coefficient is significantly positive for services related to domestic duties and services related to medical care and welfare, while it is insignificant for eating out, services related to education, and services related to communication, culture, and recreation.

Next, we run the regression using the frequency or size of price changes, which is the component of price changes. Table 15 shows the estimation results. While the coefficient

[7] As in Kishaba and Okuda (2023), we use the jobs-to-applicants ratio rather than the unemployment rate because the former captures business cycles more effectively in Japan, where employment protection is strong. Furthermore, the regional data on the unemployment rate are not as disaggregated as those on the jobs-to-applicants ratio.

is significant at the 10% level for services only when the dependent variable is the price change, the coefficient is significantly negative at the 5% level for goods, but not for services, when the dependent variable is the frequency of price changes. Although not presented in the table, this result is also true when we examine separately the frequency of upward and downward price changes. Observing goods in detail, the coefficient is significantly negative for food products and textiles. The coefficient for the size of price changes is insignificant for all categories. Table 16 shows that when the dependent variable is price dispersion, the coefficient is significantly positive for goods but not for services.

These estimation results imply the following: First, the result that the coefficient for services is significant only for the price change—but not for the frequency or size of price changes—suggests an asymmetry between the frequency of upward and downward price changes. In fact, the coefficients are positive and negative, respectively, although they are insignificant. In other words, when the effective jobs-to-applicants ratio increases, the frequency of upward price changes increases and the frequency of downward price changes decreases, resulting in a positive price change.

The second implication concerns the response regarding goods. When the effective jobs-to-applicants ratio increases, the frequency of price changes and price dispersion tend to decrease and increase, respectively. One plausible hypothesis is that when the jobs-to-applicants ratio increases, that is, when labor demand is strong, households become occupied with work, increasing the opportunity cost of shopping and decreasing demand elasticity. Consequently, firms face reduced incentives to frequently adjust their prices to optimize them. This, in turn, diminishes the likelihood of the law of one price being operative and amplifies price dispersion across various retail stores. This result is consistent with Sudo et al.'s (2018) study, wherein economic booms increases the opportunity cost of shopping, compelling retailers to curtail the frequency of temporary sales.

7 Inflation in 2022–23

Prices have been increasing worldwide around 2022–23, a period marked by the end of the COVID-19 pandemic as well as Russia's invasion of Ukraine. To investigate price developments in detail, we use the RPS data. Figures 7 to 12 illustrate the time series changes in the frequency and size of price changes and price dispersion for each category.

The solid line indicates the 50th percentile by item in each category, while the dark red and light pink ranges show the 25th–75th and 10th–90th percentile.

Specifically, Figures 7 to 9 depict the frequency of price changes in the large and medium categories. They indicate a notable increase in the frequency of price changes starting from 2022 for some but not all categories. Particularly, categories such as food products, eating out, and services related to domestic duties represent a marked increase. However, fresh food products do not display a discernible increase from 2022, suggesting that their frequency of price changes was already relatively high. Additionally, for certain other categories like textiles, petroleum products, and other industrial goods, there has been minimal change in the frequency of price changes since 2022.

Figures 10 and 11 show that the size of price changes exhibits no notable change. Figure 12 shows that price dispersion has hardly changed since 2022. In the long run, price dispersion in food products and textiles appears to be on a downward trend, whereas eating out and services related to domestic duties are on an increasing trend.

In summary, the price surge observed around 2022–23 is accompanied by a notable increase in the frequency of price changes, rather than the size of price changes. This outcome suggests that state-dependent sticky price models, such as the menu cost model, may offer a more robust framework for explaining the underlying factors driving recent price increases, as opposed to time-dependent sticky price models like the Calvo model.

8 Concluding Remarks

In this study, we have presented a diverse array of evidence on price stickiness using RPS microdata. An essential avenue for future research lies in the construction of a macroeconomic model that aligns with the empirical findings obtained from this study. Specifically, it is necessary to consider to the extent to which these facts can be explained within the simple menu cost or Calvo model, and what additional elements or complexities must be incorporated to provide a more comprehensive explanation.

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Table 1: Price Stickiness

	No. of items	Mean Weighted	Mean Unweighted	Median Unweighted	S.D. Unweighted
Frequency	511	0.215	0.249	0.155	0.283
Size	511	0.151	0.159	0.141	0.079
Price dispersion (S.D.)	511	0.257	0.268	0.230	0.181
Price dispersion (75% − 25%)	511	0.316	0.311	0.283	0.225

Note: ”Frequency” and ”size” represent the frequency of price changes on a monthly basis and the size of price changes, respectively. ”Weighted” indicates that variables are aggregated based on the CPI weights of each item.

Table 2: Price Stickiness at the Large Category Level

Category	No. of items	Weight surveyed	CPI weight	Frequency of price changes	Size
Fresh food	67	0.065	0.067	0.658	0.170
Goods (exc fresh food)	340	0.312	0.368	0.244	0.135
Goods (public)	1	0.009	0.061	0.014	0.312
Services	84	0.158	0.374	0.055	0.150
Services (public)	19	0.051	0.129	0.009	0.227
Total	511	0.594	1		

Note: No. of items represents the number of items surveyed by the RPS in each category. Weight surveyed is the sum of CPI weights for the items that are surveyed by the RPS, whereas CPI weight represents the sum of CPI weights for each category.

Table 3: Price Stickiness at the Medium Category Level

Category	No. of items	Weight surveyed	CPI weight	Frequency of price changes	Size of price changes
Fresh food	67	0.065	0.067	0.658	0.170
Other agricultural/aquatic/livestock products	3	0.006	0.006	0.244	0.100
Food products	136	0.139	0.145	0.231	0.113
Textiles	65	0.040	0.040	0.226	0.262
Petroleum products	2	0.025	0.031	0.588	0.035
Other industrial products	133	0.098	0.132	0.193	0.142
Publications	1	0.003	0.013	0.012	0.099
Eating out	24	0.049	0.049	0.022	0.108
Services related to domestic duties	27	0.045	0.046	0.011	0.148
Services related to medical care/welfare	4	0.003	0.003	0.034	0.128
Services related to education	10	0.026	0.026	0.020	0.205
Services related to communication/culture/recreation	19	0.034	0.074	0.189	0.172
Goods (public)	1	0.009	0.061	0.014	0.312
School lunch (public)	2	0.003	0.003	0.063	0.086
Services related to domestic duties (public)	3	0.008	0.050	0.013	0.267
Services related to medical care/welfare (public)	2	0.026	0.028	0.000	0.311
Services related to forwarding/communication (public)	4	0.005	0.033	0.007	0.105
Services related to education (public)	4	0.004	0.004	0.009	0.336
House rent	0		0.026		
Imputed rent	0		0.150		
House rent (public)	0		0.002		
Services related to culture/recreation (public)	0		0.009		
Total	507	0.590	1.000		

Note: See notes in Table 2.

Table 4: Sensitivity of Measurements of Price Stickiness to Item and Person Changes

Category	Frequency				Size	
item changes excluded	yes	no	yes	no	yes	no
person changes excluded	yes	no	no	yes	yes	no
Fresh food	0.658	0.679	0.677	0.659	0.170	0.181
Other agricultural/aquatic/livestock products	0.244	0.254	0.254	0.244	0.100	0.101
Food products	0.231	0.245	0.241	0.234	0.113	0.156
Textiles	0.226	0.251	0.245	0.231	0.262	0.275
Petroleum products	0.588	0.600	0.594	0.594	0.035	0.035
Other industrial products	0.193	0.213	0.204	0.202	0.142	0.180
Publications	0.012	0.012	0.012	0.012	0.099	0.099
Eating out	0.022	0.033	0.032	0.022	0.108	0.148
Services related to domestic duties	0.011	0.016	0.015	0.012	0.148	0.444
Services related to medical care/welfare	0.034	0.036	0.036	0.034	0.128	0.161
Services related to education	0.020	0.021	0.020	0.021	0.205	0.208
Services related to communication/culture/recreation	0.189	0.193	0.191	0.191	0.172	0.183
Goods (public)	0.014	0.014	0.014	0.014	0.312	0.312
School lunch (public)	0.063	0.063	0.063	0.063	0.086	0.086
Services related to domestic duties (public)	0.013	0.013	0.013	0.013	0.267	0.267
Services related to medical care/welfare (public)	0.000	0.000	0.000	0.000	0.311	0.300
Services related to forwarding/communication (public)	0.007	0.007	0.007	0.007	0.105	0.105
Services related to education (public)	0.009	0.009	0.009	0.009	0.336	0.336

Table 5: Sensitivity of Measurements of Price Stickiness to Region Aggregation

Aggregated Items	Baseline No	City	Prefecture
"Udon", Japanese noodles (eating out)	0.026	0.064	0.149
Chinese noodles (eating out)	0.026	0.054	0.154
"Soba", Japanese noodles (eating out)	0.031	0.113	0.113
"Okinawa" noodles (eating out)	0.025	0.032	0.162
Spaghetti (eating out)	0.033	0.115	0.115
Sushi (eating out)-B	0.028	0.070	0.070
Sushi (eating out)-A	0.034	0.065	0.065
Tempura bowls (eating out)	0.030	0.111	0.111
Curry & rice (eating out)	0.025	0.054	0.156
"Gyoza" (eating out)	0.026	0.082	0.082
Hamburgers (eating out)	0.043	0.089	0.089
Beef bowls (eating out)	0.039	0.102	0.102
Hamburg steaks (eating out)	0.047	0.155	0.155
Pork cutlet set meals (eating out)	0.035	0.123	0.123
Delivered pizza	0.053	0.141	0.141
Broiled meat (eating out)	0.037	0.086	0.086
Ginger pork set meals (eating out)	0.040	0.134	0.134
Sandwiches (eating out)	0.027	0.101	0.101
Coffee (eating out)-A	0.024	0.061	0.122
Doughnuts (eating out)	0.026	0.037	0.037
Fried chickens (eating out)	0.005	0.009	0.009
Coffee (eating out)-B	0.021	0.047	0.047
Beer (eating out)	0.036	0.088	0.172
"Yakitori", grilled chicken (eating out)	0.035	0.134	0.134

Note: The table presents the frequency of price changes on a monthly basis. City and prefecture indicate the frequency of price changes when we calculate the unweighted mean of prices in each city and prefecture, respectively, and then the frequency of changes in the mean price from the previous month.

Table 6: Relation among Frequency, Size, and Price Dispersion

	Dependent variable							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Size		Price dispersion					
			(S.D.)	(S.D.)	(75-25%)	(S.D.)	(S.D.)	(S.D.)
Frequency	0.006	-0.004	0.051**	0.089**	0.07	-0.005	-0.02	-0.015
	(0.014)	(0.027)	(0.020)	(0.036)	(0.046)	(0.066)	(0.053)	(0.087)
Size			0.662***	0.843***	1.274***	0.522	0.833***	0.796*
			(0.092)	(0.131)	(0.143)	(0.325)	(0.208)	(0.449)
Fixed effects	no	category	no	category	category	no	no	no
Data	item	item	item	item	item	category	category	category
Observations	505	505	505	505	505	19	18	19
Adj. R2	-0.002	0.407	0.089	0.087	0.146	0.115	0.547	0.157

Note: Figures in parentheses indicate standard errors.

Table 7: Panel-data Regression of Size on Frequency

	Size			
	(1)	(2)	(3)	(4)
	Fresh food	Goods (exc fresh food)	Services	Services (public)
Frequency	-0.012	0.004*	0.046***	0.018
	(0.010)	(0.002)	(0.014)	(0.015)
Fixed effects	pref, item, month			
Observations	135,144	851,959	27,401	2,621
Adjusted R2	0.147	0.218	0.142	0.323

Note: Figures in parentheses indicate standard errors, which are clustered at the item level.

Table 8: Panel-data Regression of Price Dispersion on Frequency and Size

	Price dispersion (S.D.)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fresh food		Goods (exc fresh food)		Services		Services (public)	
Freq	0.014*		-0.015***		-0.085***		-0.047*	
	(0.007)		(0.002)		(0.015)		(0.026)	
Freq up		0.001		-0.025***		-0.093***		-0.056
		(0.007)		(0.003)		(0.015)		(0.032)
Freq down		0.029***		-0.006**		-0.068***		-0.039
		(0.008)		(0.003)		(0.013)		(0.025)
Size	0.161***	0.169***	0.102***	0.106***	0.095***	0.096***	0.069***	0.070***
	(0.007)	(0.007)	(0.005)	(0.005)	(0.010)	(0.010)	(0.015)	(0.015)
Fixed effects	pref, item, month							
Observations	135,132	135,132	850,518	850,518	27,181	27,181	2,439	2,439
Adjusted R2	0.297	0.3	0.498	0.499	0.353	0.353	0.482	0.482

Note: Figures in parentheses indicate standard errors, which are clustered at the item level.

Table 9: Dependence of Log Price on City Weight

Category	Estimate	S.E.	t	p	Observations	No of items	R2
Fresh food	0.009	(0.004)	2.553	0.017	11,045	25	0.957
Other agricultural/aquatic/livestock products	0.018	(0.004)	4.040	0.056	1,568	3	0.980
Food products	0.009	(0.003)	3.035	0.003	36,645	120	0.957
Textiles	-0.002	(0.005)	-0.503	0.619	6,583	27	0.974
Other industrial products	0.001	(0.002)	0.518	0.606	24,933	113	0.995
Eating out	0.003	(0.007)	0.401	0.694	3,476	17	0.893
Services related to domestic duties	0.057	(0.016)	3.539	0.002	3,654	20	0.944
Services related to medical care/welfare	0.085	(0.027)	3.207	0.085	332	3	0.993
Services related to education	0.066	(0.041)	1.620	0.140	4,208	10	0.924
Services related to communication/culture/recreation	0.096	(0.021)	4.657	0.000	2,418	17	0.982
Services related to domestic duties (public)	-0.074	(0.033)	-2.225	0.156	756	3	0.322
Services related to forwarding/communication (public)	-0.022	(0.014)	-1.633	0.244	1,325	3	0.147

Note: S.E. indicates standard errors, which are clustered at the item level.

Table 10: Dependence of the Frequency of Price Changes on City Weight

Category	Estimate	S.E.	t	p	Observations	No of items	R2
Fresh food	0.007	(0.003)	2.373	0.026	11,045	25	0.782
Other agricultural/aquatic/livestock products	0.024	(0.003)	6.909	0.020	1,568	3	0.136
Food products	0.009	(0.002)	5.973	0.000	36,645	120	0.522
Textiles	0.005	(0.002)	3.004	0.006	6,583	27	0.470
Other industrial products	0.010	(0.001)	8.231	0.000	24,933	113	0.797
Eating out	0.001	(0.000)	2.593	0.020	3,476	17	0.106
Services related to domestic duties	0.001	(0.000)	3.379	0.003	3,654	20	0.125
Services related to medical care/welfare	-0.001	(0.002)	-0.363	0.751	332	3	0.429
Services related to education	0.001	(0.001)	1.846	0.098	4,212	10	0.242
Services related to communication/culture/recreation	0.009	(0.003)	3.114	0.007	2,417	17	0.629
Services related to domestic duties (public)	0.001	(0.000)	5.285	0.034	951	3	0.152
Services related to forwarding/communication (public)	0.001	(0.000)	3.571	0.070	1,325	3	0.032
Services related to education (public)	0.001	(0.000)	1.531	0.223	3,632	4	0.128
Services related to culture/recreation (public)	-0.001	(0.004)	-0.352	0.748	295	4	0.117

Note: S.E. indicates standard errors, which are clustered at the item level.

Table 11: Dependence of the Size of Price Changes on City Weight

Category	Estimate	S.E.	t	p	Observations	No of items	R2
Fresh food	0.002	(0.001)	2.966	0.007	11,040	25	0.319
Other agricultural/aquatic/livestock products	0.001	(0.001)	1.834	0.208	1,568	3	0.062
Food products	-0.002	(0.001)	-3.222	0.002	36,621	120	0.344
Textiles	0.005	(0.002)	2.380	0.025	6,537	27	0.226
Other industrial products	-0.002	(0.001)	-1.715	0.089	24,911	113	0.525
Eating out	0.006	(0.002)	2.485	0.024	3,272	17	0.040
Services related to domestic duties	0.001	(0.004)	0.167	0.869	2,963	20	0.492
Services related to medical care/welfare	0.001	(0.004)	0.218	0.847	213	3	0.239
Services related to education	-0.007	(0.019)	-0.349	0.735	2,024	10	0.087
Services related to communication/culture/recreation	-0.001	(0.009)	-0.069	0.946	2,203	17	0.270
Services related to domestic duties (public)	-0.008	(0.007)	-1.120	0.464	481	2	0.068
Services related to forwarding/communication (public)	0.034	(0.003)	9.991	0.010	733	3	0.095
Services related to education (public)	-0.046	(0.014)	-3.285	0.081	1,686	3	0.053
Services related to culture/recreation (public)	-0.042	(0.018)	-2.265	0.152	133	3	0.414

Note: S.E. indicates standard errors, which are clustered at the item level.

Table 12: Dependence of Price Dispersion on City Weight

Category	Estimate	S.E.	t	p	Observations	No of items	R2
Fresh food	-0.002	(0.001)	-1.599	0.123	11,045	25	0.079
Other agricultural/aquatic/livestock products	0.004	(0.000)	13.315	0.006	1,568	3	0.054
Food products	-0.002	(0.001)	-1.917	0.058	36,645	120	0.268
Textiles	-0.004	(0.002)	-2.198	0.037	6,583	27	0.290
Other industrial products	-0.002	(0.001)	-2.511	0.013	24,933	113	0.418
Eating out	0.002	(0.004)	0.509	0.618	3,476	17	0.212
Services related to domestic duties	0.009	(0.006)	1.575	0.132	3,654	20	0.169
Services related to medical care/welfare	0.027	(0.013)	2.023	0.180	332	3	0.122
Services related to education	-0.016	(0.014)	-1.143	0.282	4,208	10	0.179
Services related to communication/culture/recreation	0.011	(0.012)	0.935	0.364	2,418	17	0.343
Services related to domestic duties (public)	0.001	(0.005)	0.297	0.795	756	3	0.182
Services related to forwarding/communication (public)	0.004	(0.003)	1.580	0.255	1,325	3	0.180

Note: S.E. indicates standard errors, which are clustered at the item level.

Table 13: Regression of the Phillips Curve (Large Category)

	100 dlog(price)			
	(1)	(2)	(3)	(4)
	Fresh food	Goods (excl. fresh food)	Services	Services (public)
Job	-0.014	-0.036	0.083*	-0.202
	(0.072)	(0.025)	(0.043)	(0.245)
Fixed effects	pref, item, month			
Observations	149,962	1,781,744	407,267	61,083
Adjusted R2	0.118	0.039	0.01	0.009

Note: Figures in parentheses indicate standard errors, which are clustered at the item level.

Table 14: Regression of the Phillips Curve (Medium Category)

	Category	Estimate on job	(S.E.)	No. of obs	Adj R2
(1)	Fresh food	-0.014	(0.072)	149,962	0.118
(2)	Other agricultural/aquatic/livestock products	0.045	(0.064)	16,873	0.065
(3)	Food products	-0.037	(0.024)	771,626	0.07
(4)	Textiles	-0.194	(0.133)	248,679	0.096
(5)	Petroleum products	0.082	(0.160)	11,750	0.73
(6)	Other industrial products	0.019	(0.030)	729,150	0.019
(7)	Publications	-0.308	–	3,665	0.169
(8)	Eating out	-0.057	(0.061)	120,691	0.008
(9)	Services related to domestic duties	0.174**	(0.065)	144,305	0.034
(10)	Services related to medical care/welfare	0.295**	(0.075)	13,320	-0.0001
(11)	Services related to education	0.334	(0.233)	35,886	0.015
(12)	Services related to communication/culture/recreation	0.089	(0.106)	93,064	0.018
(13)	School lunch (public)	-1.929*	(0.275)	7,331	0.076
(14)	Services related to domestic duties (public)	0.132	(0.155)	10,913	0.1
(15)	Services related to medical care/welfare (public)	-0.703	(0.346)	5,404	0.867
(16)	Services related to forwarding/communication (public)	-0.267	(0.214)	12,010	-0.006
(17)	Services related to education (public)	0.322	(0.314)	11,442	0.004
(18)	Services related to culture/recreation (public)	0.351	(0.614)	13,982	0.076

Note: Figures in parentheses indicate standard errors, which are clustered at the item level.

Table 15: Regression of the Phillips Curve (Frequency of Price Changes)

	Frequency of price changes			
	(1)	(2)	(3)	(4)
	Fresh food	Goods (exc fresh food)	Services	Services (public)
Job	0.012	-0.010***	-0.001	-0.001
	(0.0100)	(0.0030)	(0.0030)	(0.0040)
Fixed effects		pref, item, month		
Observations	152,348	1,809,645	412,720	62,788
Adjusted R2	0.688	0.356	0.187	0.123

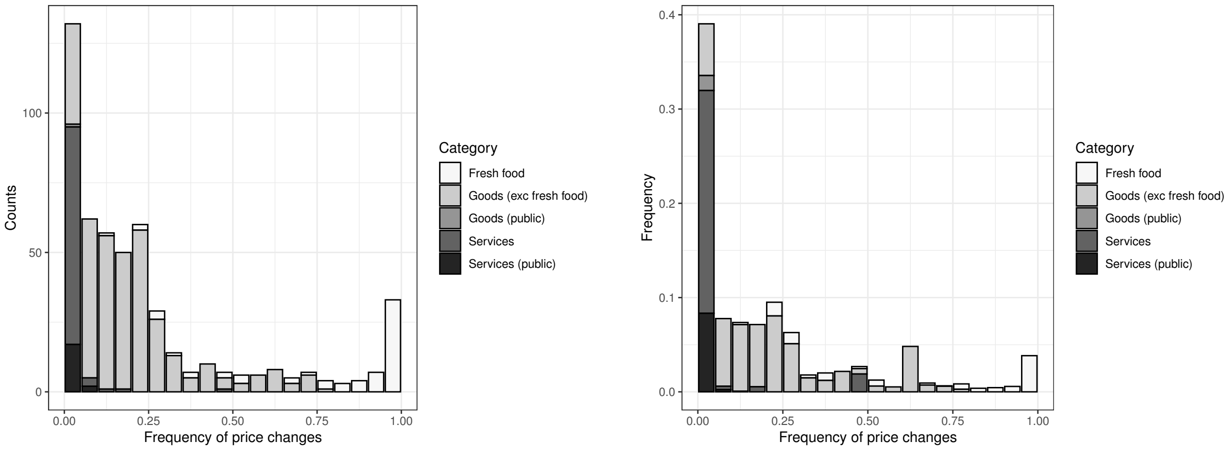
Note: Figures in parentheses indicate standard errors, which are clustered at the item level.

Table 16: Regression of the Phillips Curve (Price Dispersion)

	Price dispersion (S.D.)			
	(1)	(2)	(3)	(4)
	Fresh food	Goods (exc fresh food)	Services	Services (public)
Job	0.005	0.008***	0.011	-0.041
	(0.0060)	(0.0030)	(0.0090)	(0.0310)
Fixed effects	pref, item, month			
Observations	153,445	1,829,413	408,721	43,281
Adjusted R2	0.252	0.447	0.253	0.45

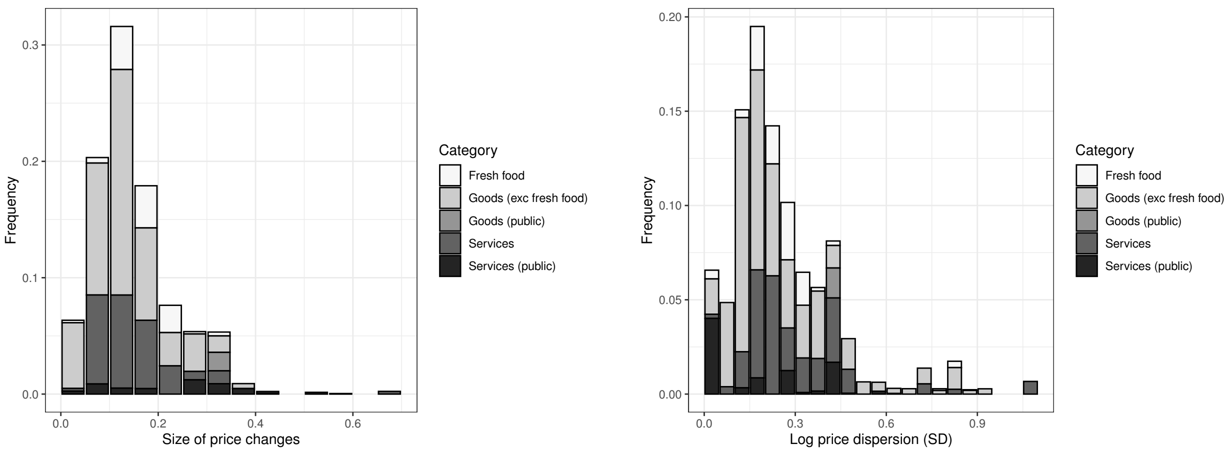
Note: Figures in parentheses indicate standard errors, which are clustered at the item level.

Figure 1: Distribution of the Frequency of Price Changes



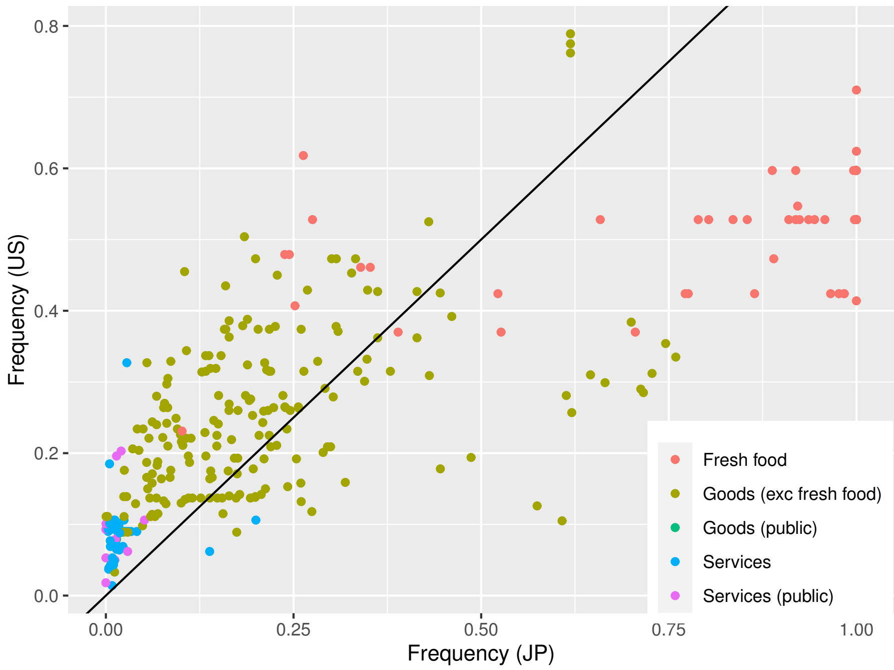
Note: The right-hand side panel is the weighted histogram based on the CPI weight of each item.

Figure 2: Distribution of the Size of Price Changes and Price Dispersion



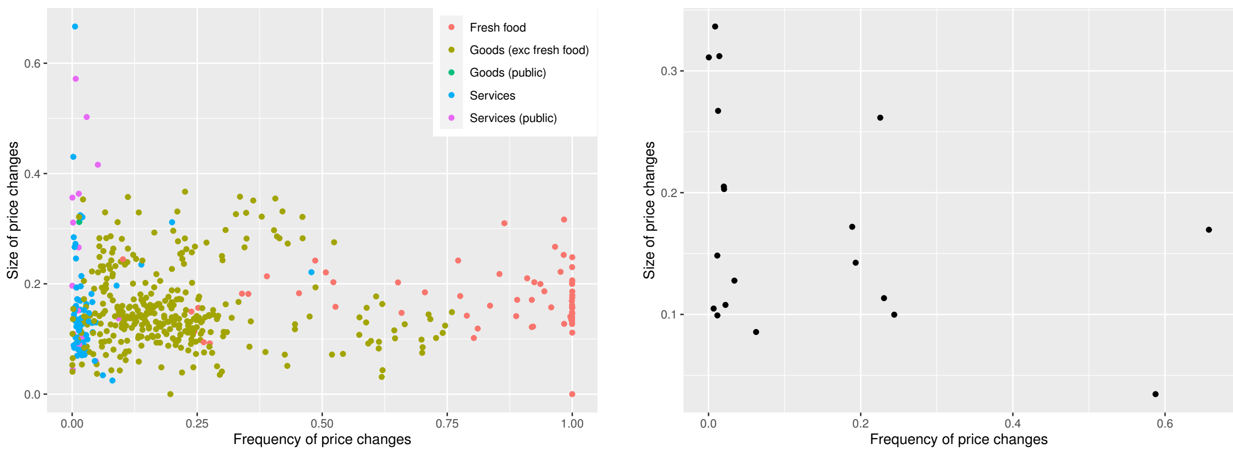
Note: The distribution is weighted based on the CPI weight of each item.

Figure 3: Comparison of the Frequency of Price Changes between Japan and the U.S.



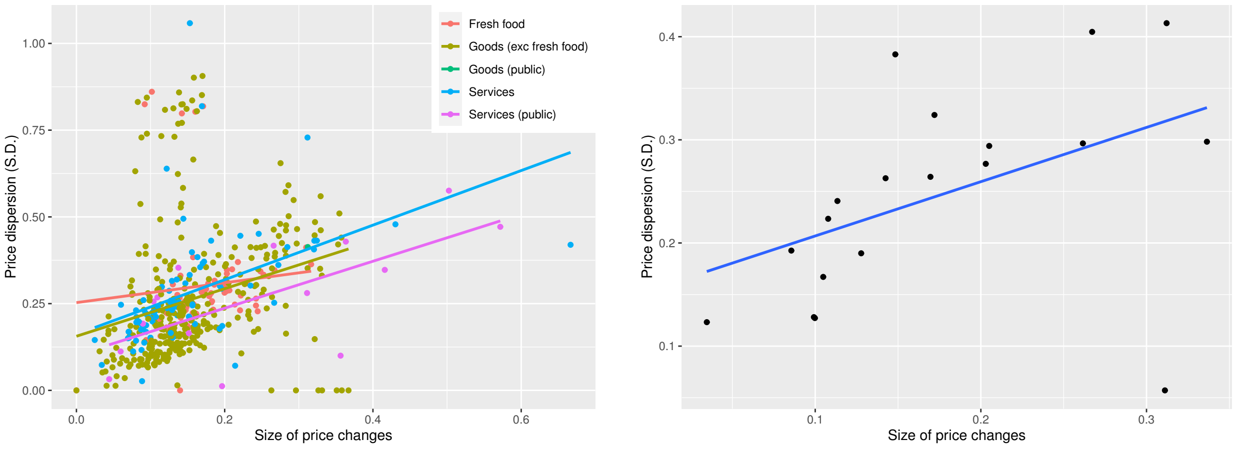
Note: The solid line indicates the 45 degree line.

Figure 4: Relationship between the Frequency and Size of Price Changes



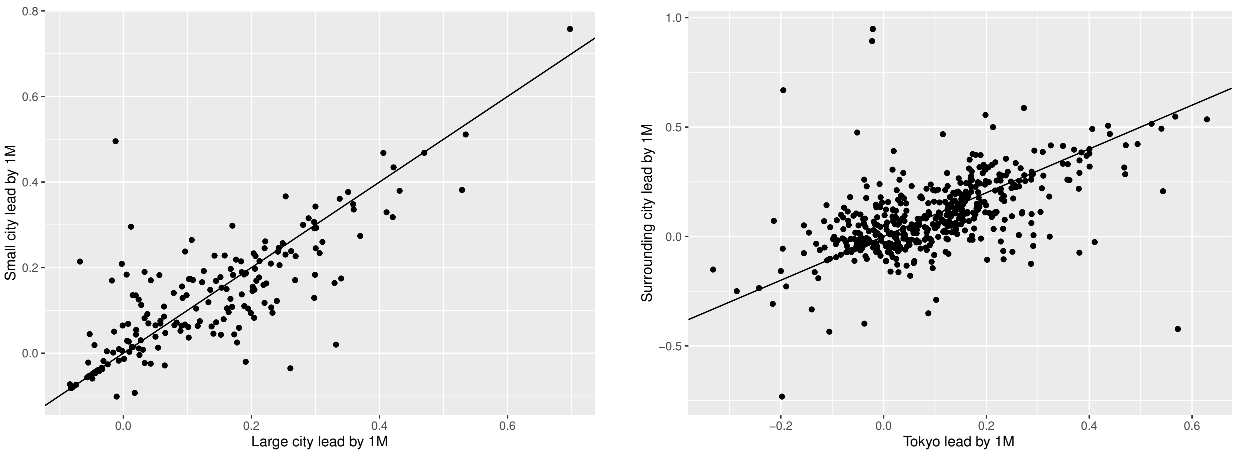
Note: In the left- and right-hand side panels, each dot represents an item and a medium category, respectively.

Figure 5: Relationship between the Size of Price Changes and Price Dispersion



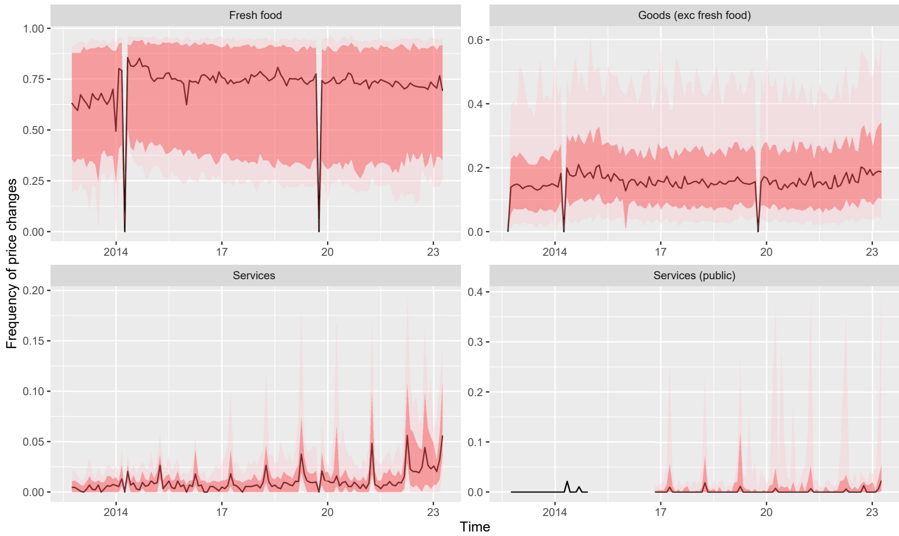
Note: In the left- and right-hand side panels, each dot represents an item and a medium category, respectively. The solid lines represent the linear regression lines.

Figure 6: Lead-lag Correlation between Cities



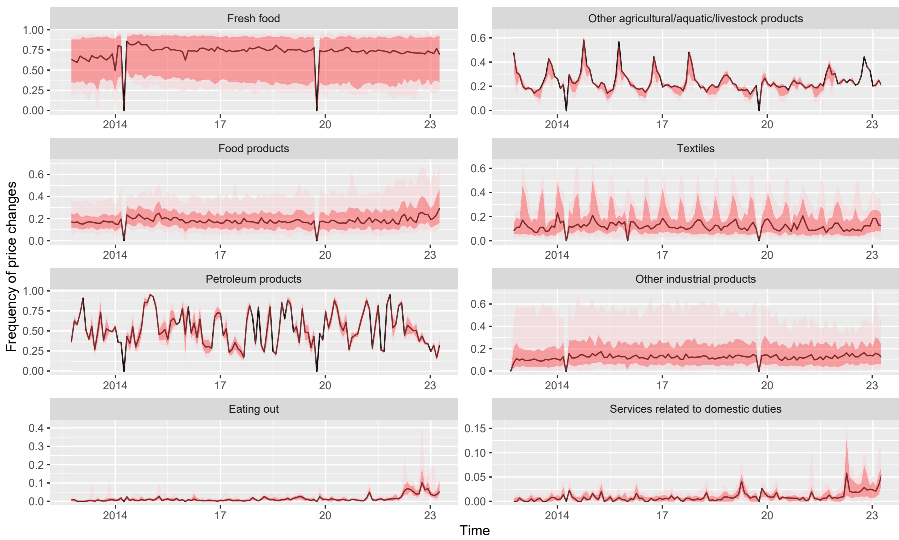
Note: To draw the figures, first, we calculate the frequency of price changes per month, item, and region. For regions, we select a large city and a small city A based on the RPS classification in the left-hand side panel and Tokyo wards and major large cities in the surrounding prefectures (Saitama City, Yokohama City, and Chiba City) in the right-hand side panel. Second, for each item, we calculate correlation coefficients for pairs of a large city and a small city A (left-panel) and for pairs of a Tokyo ward and a major metropolitan area in the surrounding prefectures (right-panel). Correlation coefficients are not calculated simultaneously, but are shifted by one month from each other. Each dot represents an item and the solid lines represent the 45-degree lines.

Figure 7: Time-Series Changes in the Frequency of Price Changes (Large Category)



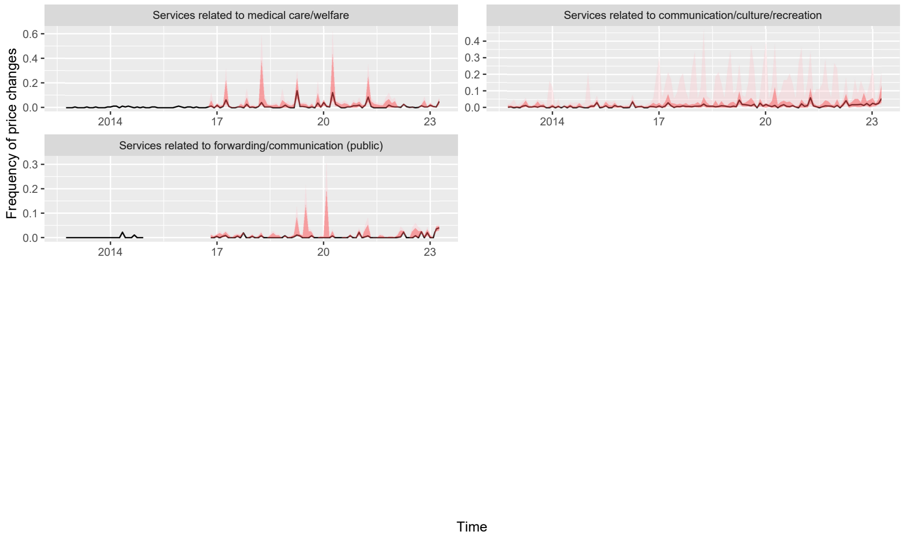
Note: The solid lines indicate the median (50%) based on items in each category, whereas the dark and light red areas indicate 25–75 and 10–90 percentile ranges, respectively.

Figure 8: Time-Series Changes in the Frequency of Price Changes (Medium Category)



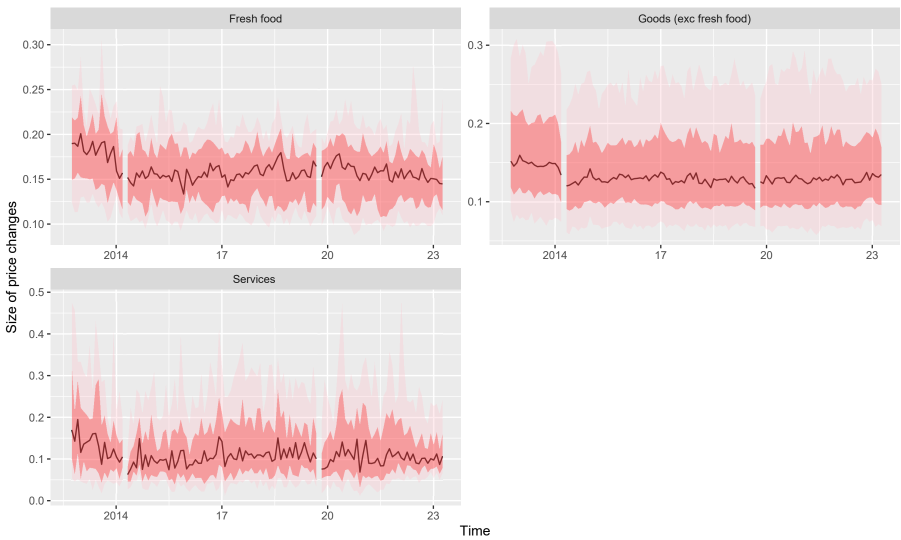
Note: The solid lines indicate the median (50%) based on items in each category, whereas the dark and light red areas indicate 25–75 and 10–90 percentile ranges, respectively.

Figure 9: Time-Series Changes in the Frequency of Price Changes (Medium Category 2)



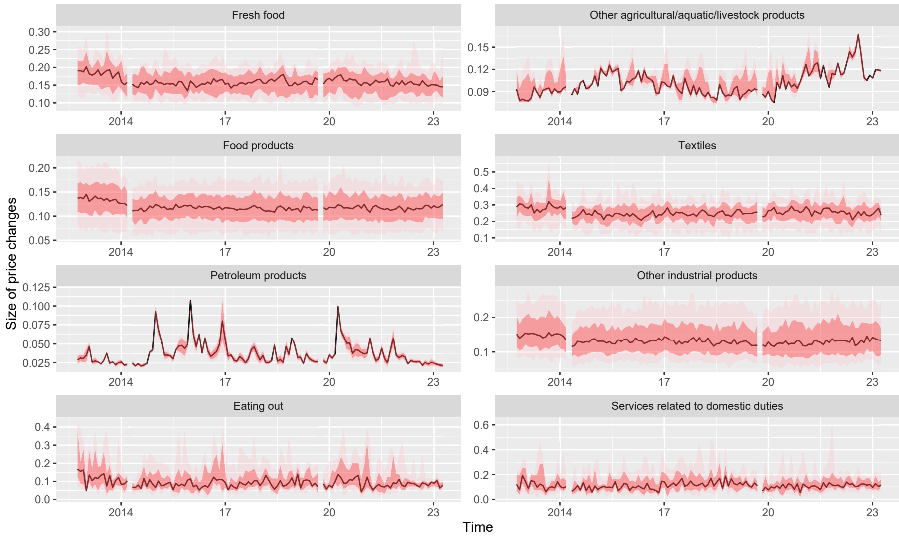
Note: The solid lines indicate the median (50%) based on items in each category, whereas the dark and light red areas indicate 25–75 and 10–90 percentile ranges, respectively.

Figure 10: Time-Series Changes in the Size of Price Changes (Large Category)



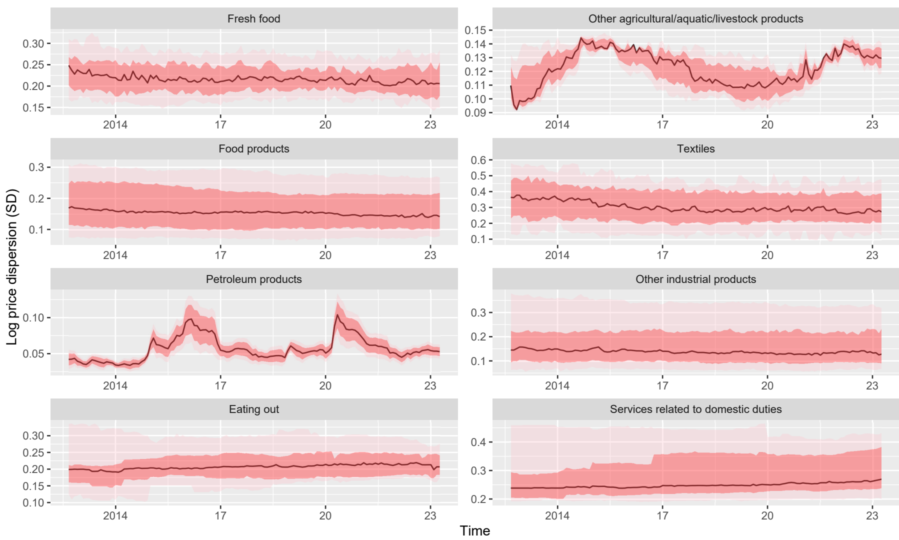
Note: The solid lines indicate the median (50%) based on items in each category, whereas the dark and light red areas indicate 25–75 and 10–90 percentile ranges, respectively.

Figure 11: Time-Series Changes in the Size of Price Changes (Medium Category)



Note: The solid lines indicate the median (50%) based on items in each category, whereas the dark and light red areas indicate 25–75 and 10–90 percentile ranges, respectively.

Figure 12: Time-Series Changes in Price Dispersion (S.D., Medium Category)



Note: The solid lines indicate the median (50%) based on items in each category, whereas the dark and light red areas indicate 25–75 and 10–90 percentile ranges, respectively.