Closely Competing Firms and Price Adjustment: Evidence from an Online Marketplace

Takayuki Mizuno[*]   Makoto Nirei[†]   Tsutomu Watanabe[‡]

First draft: August 19, 2009

This version: June 9, 2010

Abstract

We investigate retailers' price setting behavior using a unique dataset containing by-the-second records of prices offered by closely competing retailers on a major Japanese price comparison website. First, we find that, when the average price of a product across retailers falls rapidly, the *frequency* of price adjustments increases, and the *size* of price adjustments becomes larger. Second, we find positive autocorrelation in the *frequency* of price adjustments, implying that there tends to be clustering where price adjustments occur in succession. In contrast, there is no such autocorrelation in the *size* of price adjustments. These two findings indicate that the behavior of competing retailers is characterized by state-dependent pricing rather than time-dependent pricing.

JEL Classification Number: E30
Keywords: price rigidities; time-dependent pricing; state-dependent pricing; adjustment hazard function; real rigidities; strategic complementarities in price setting; online markets

1 Introduction

Since the seminal study by Bils and Klenow (2004), there has been extensive research on price stickiness using micro price data. One vein of research along these lines concentrates on price adjustment events and examines the frequency with which such events occur. An important finding of such studies is that price adjustment events occur quite frequently. Using

raw data of the U.S. consumer price index (CPI), Bils and Klenow (2004) report that the median frequency of price adjustments is 4.3 months. Using the same U.S. CPI raw data, Nakamura and Steinsson (2008) report that when sales are excluded, prices are adjusted with a frequency of once every 8 to 11 months. Similar studies focusing on other countries include Dhyne et al. (2006) for the euro area and Higo and Saita (2007) for Japan.

The frequency measure of price changes is an indicator of price stickiness at the micro level. Most studies find that this micro price stickiness is too low to explain the price rigidity observed at the macro level. Assuming that the measurements of both micro and macro stickiness are correct, a possible explanation for this discrepancy is real rigidities or strategic complementarities in price setting, as has been advocated by Ball and Romer (1990), Kimball (1995), and others. In Kimball's setting, where price adjustment events are assumed to occur according to a Poisson process, firms with an opportunity to adjust their prices are influenced by other firms that do not adjust prices, therefore keeping the extent of the price adjustment small. Given that the fraction of adjusters remains unchanged, this implies that prices are stickier at the macro level.

This means that to understand the extent of macro price stickiness, it is insufficient to only examine the frequency of micro price adjustments; instead, it is also necessary to examine the size of price adjustment and the extent to which firms' price changes are correlated. To do so, what is important is to collect price data of competing firms, that is, price data for individual firms whose pricing behavior is potentially correlated with each other. Unfortunately, such data are rarely available. For the compilation of CPI statistics, for example, a particular retailer is chosen to represent a particular region for a particular product and sales price data are then collected from that retailer. This means that it is virtually impossible to obtain price data from competing retailers from CPI raw data. Another potential source is scanner data, but as far as we are aware, there exists no comprehensive dataset comprising prices for competing retailers.

In order to investigate the price setting behavior of retailers that directly compete with each other, we use online market data in this paper. Specifically, the data we use are the

selling prices offered by retailers on Kakaku.com, a major price comparison site in Japan. Transactions on this site concentrate on consumer electronics such as TV sets, video equipment, digital cameras, etc. For example, for the AQUOS LC-32GH2, a liquid crystal television model made by Sharp, prices were provided by about 100 firms. These retailers have registered with Kakaku.com beforehand and have entered a contract stating that they will pay fees to Kakaku.com reflecting the number of customers transferred to their website via Kakaku.com. These 100 retailers monitor at what prices the other retailers offer the same product at any particular moment and, based on this, adjust the price at which they offer that product themselves. Thus, these retailers can be said to be engaged in moment-by-moment price competition in the virtual market provided by the price comparison site.

The dataset consists of the records, with a time stamp up to the second, of all prices offered by each of the competing retailers for all products over the two year sample period. It allows us to track prices of a single product, which is identified by its barcode, offered by competing retailers over time. However, like most of the micro price data used in previous studies, our dataset does not contain any information about shocks, such as shocks to marginal costs, so that we cannot tell whether comovements in prices offered by different retailers come from strategic interaction between them or common shocks. Still, data on the size, frequency, and correlation of price changes can help to discriminate between different theories.

Time-dependent pricing models with strategic complementarities imply that after a common shock to marginal costs, there will be multiple rounds of price adjustments, in which the size of successive adjustments is small. The probability of price adjustments is exogenously given in those models, so that the presence of multiple rounds of price adjustments implies that it takes longer until the entire process of price adjustments is completed. Thus those time dependent pricing models imply that the size of price changes is persistent in the sense that it is positively correlated with its own past values, but that the frequency of price changes is not persistent. State-dependent pricing models with strategic complementarities imply that the number of price adjustments per period increases after a cost shock, that is, "temporal

3

agglomeration" or clustering in price adjustments emerges.[1/2] Thus those state dependent pricing models imply that both the size and the frequency of price adjustments are persistent. Empirical evidence on the persistence in the size of price adjustments is mixed. Specifically, Bils et al. (2009) investigate this by employing raw data of the U.S. CPI, but fail to find positive autocorrelation in the size of price adjustments.[3] In contrast, Gopinath and Itskhoki (2009) find that exchanges rate changes pass-through into import prices only gradually and interpret this as evidence for multiple rounds of price adjustments due to strategic complementarities. Turning to the persistence in the frequency of price adjustments, as far as we are aware, there do not exist any empirical papers that directly investigate this, partly due to the absence of datasets that contain information regarding pricing behavior of competing firms.[4] In this paper, we will examine persistence both in the frequency and the size of price changes by making full use of our dataset.

The main findings of this paper are as follows. First, we find that, when the average price of a product across retailers falls rapidly, the frequency of price adjustments increases, and the size of price adjustments becomes larger. This result suggests that pricing behavior of competing retailers is characterized by state-dependent pricing, rather than time-dependent pricing. Second, we find positive and significant autocorrelation in the frequency of price adjustments, implying that there tends to be clustering where, once a price adjustment occurs, such adjustments occur in succession. In contrast, we fail to find any positive autocorrelation in the size of price adjustments. The lack of persistence in the size of price adjustments

---

[1]Ball and Romer (1990) investigate the role of strategic complementarities in an economy with menu costs, in which not only the size but also the timing of price adjustments is endogenously determined. They show that, provided that other firms adjust their prices, it would be optimal for a firm to adjust its price, yielding a positive correlation between price adjustments by one firm and price adjustments by rival firms.

[2]It is well known that such clustering occurs in a more general setting in which agents make discrete decisions (price adjustment is an example of such discrete decisions) and there exist strategic complementarities among them. Agents have an incentive to bunch discrete decisions in that situation. See Cooper and Haltiwanger (1996) for a survey of empirical studies that look for clustering in various economic activities such as machine replacement, investment, and so on, as evidence for strategic complementarities.

[3]More precisely, what they did was to estimate "reset price inflation" (i.e., the rate of change of desired prices) and to examine its persistence in addition to persistence in the rate of inflation as commonly defined. They fail to find positive autocorrelation in both of the two inflation variables.

[4]Indirect evidence is provided by Klenow and Kryvtsov (2008), who look for bunching of price changes (or price synchronization) using raw data of the U.S. CPI for 1988-2003 and find that there is little price bunching in the sense that the number of price adjustments does not fluctuate much, at least during this period of low inflation. They did not examine persistence in the number of price adjustments.

that we find, a result that is similar to what Bils et al. (2009) find using raw data of the CPI, contradicts time-dependent pricing models with strategic complementarities. Third and finally, we find that the probability of price adjustments for a given retailer increases with the number of previous adjustments made by his rivals since his last price adjustment.

The rest of the paper is organized as follows. Section 2 provides a description of the Kakaku.com dataset used in this paper and discusses some of the characteristics of these data. In Section 3, we present stylized facts about price adjustments in this market. In Section 4, we conduct a simulation analysis using a model of state-dependent pricing with strategic complementarities based on Caballero and Engel (2007) in order to see whether the facts found in Section 3 can be replicated by the model. Section 5 concludes the paper.

2 Data Description

2.1 Overview

The data we use in this paper are from Kakaku.com, a major Japanese price comparison website. The website is operated by Kakaku.com, Inc., and at present about 1,300 retailers use the site as part of their sales activities. A wide range of products is offered through the website, but the most important are consumer electronics and personal computers, and if items with a different barcode are counted as separate products, about 300,000 products are offered. The number of monthly users is about 12 million.

By visiting the website, users of Kakaku.com can obtain information on the characteristics of a product they are interested in, find a list of retailers offering that product, and the price at which each retailer offers that product. In addition, users can also obtain information on the characteristics of retailers such as whether they charge delivery fees, whether they accept credit card payment, whether they have an offline shop, and retailer ratings by customers who have used the retailer. Consumers visiting Kakaku.com use this information to choose a retailer from which to purchase that product and then click a button on the Kakaku.com website saying "Go to retailer." They are then transferred to the website of the retailer, where they go through the retailer's sales procedure and finally purchase the product.

There are various types of price comparison websites and some focus on gathering, on their own, prices advertised on internet websites and posting a list of these. However, different from this type of price comparison websites, the special characteristic of Kakaku.com is that Kakaku.com, Inc., and each retailer enter a contract (on the payment of fees depending on transferred customers, etc.) before any prices are listed. Therefore, retailers are well-informed about what other retailers have registered with Kakaku.com. Moreover, based on information sent to them by Kakaku.com, Inc., retailers check three or four times a day, or more frequently, the prices offered by other retailers, the overall rank of their own price, whether the number of customers transferred to their own site is large or small, and, if necessary, adjust their own price.

The dataset used in this paper consists of the records, with a time stamp up to the second, of all prices offered by each retailer (for a total of around 4 million records) and the history of customer clicks on the "Go to retailer" button (around 24 million records) for all products offered during the 731 days from November 1st, 2006, to October 31st, 2008.[5]

This is not the first study to use prices from price comparison sites. However, few studies have used a dataset that includes information on how the price at which competing retailers offer a product changes over time, and which retailer consumers click on. The dataset closest to the one in this paper is the one used by Baye et al. (2009) from a price comparison site in the United Kingdom. However, their dataset consists of daily aggregated data and does not allow observations on competition between retailers on an hour-by-hour, minute-by-minute, and, in some cases, even second-by-second basis.

Figure 1 shows an example of the fluctuations in the prices at which three competing retailers were offering a liquid crystal TV made by Sharp (AQUOS LC-32GH2). The figure illustrates the following. First, there is a strong downward trend in the price for this product, and within a period of about 50 days, the price fell from 130,000 yen to a little below

---

[5]Of course it is important to note that just because the "Go to retailer" button was clicked on, this does not necessarily mean that this ultimately resulted in a purchase. However, looking at the correlation between the number of customers referred from Kakaku.com and information on the number of actual sales obtained from scanner data for several of the retailers registered with Kakaku.com, it can be confirmed that this is extremely high. This result shows that the number of clicks is a sufficiently useful proxy for the actual number of sales.

120,000 yen. However, what also becomes clear is that the retailers did not continuously lower prices day-by-day. Rather, after maintaining a particular price level for several days or weeks, they lowered the price discontinuously by several hundred or several thousand yen. Then, soon thereafter, they again maintained the same price level. This occurred repeatedly. In sum, price adjustment events are infrequent in the sense that they do not occur every day and time intervals between two consecutive events are irregular. When they do occur, price adjustments are discontinuous in the sense that the size of each adjustment is typically far above zero. These two properties are in line with patterns shown in previous studies using CPI raw data or scanner data.[6] Second, the three retailers do not adjust prices at the same time but instead each adjusts their price at a different time and to a different extent. Although the prices offered by the three retailers overall show the same trend, a closer look reveals that the price gap between the retailers fluctuates, and that competition is fierce, with first one retailer and then the other taking the lead.

2.2 Frequency of price adjustments

Figure 2 (a) shows the distribution of the price duration (that is, the interval from one price change until the next price change) for the AQUOS LC-32GH2 liquid crystal TV. The data we are using here are for 230 days starting from November 2006, during which this particular model was available in this market. The number of retailers providing a price for this product during this period is not fixed, but on average there are 40 retailers. We use all the price spells for these retailers. Note that the period from when a retailer begins to offer this product until it first changes the price is not regarded as a price spell. We similarly exclude the period immediately before a retailer stops offering a product.

In the figure, the horizontal axis shows the price duration, while the vertical axis shows the corresponding value of the cumulative distribution function (CDF). For example, the value on the vertical axis corresponding to a price duration of 10 days is 0.04, indicating

---

[6]Studies using CPI raw data or scanner data report that sales (that is, temporary price drops) occur frequently. However, at least on the basis of Figure 1, it appears that the retailers on Kakaku.com do not conduct sales. In the dataset used in our paper, sales cannot be observed as frequently as in the case of offline retailers.

that the share of price spells of 10 days or more in the total is 4 percent. The average price duration is 1.93 days, and the median is 0.34 days. In other words, on average, the probability that a price adjustment event occurs on any given day is 0.518 (=1/1.93). If price adjustment events would occur according to a Poisson process, price duration would follow an exponential distribution. Because the vertical axis here is shown in logarithmic scale, if the price duration follows an exponential distribution, the measured CDF should form a straight line. However, as can be seen in the figure, the CDF takes a convex shape.

In previous research using micro price data, it is repeatedly reported that the hazard function is downward sloping, that is, the longer the time since the last price adjustment, the lower is the probability of an adjustment event occurring. Figure 2 (b), which presents the hazard function estimated from our data,[7] shows that the same is the case here. However, previous studies measure hazard functions using pooled data for several products, so it is possible that the downward sloping hazard function may be the result of heterogeneity in price adjustment probabilities across different products. In contrast, the price spells used in Figure 2 (b) are collected for only one product, so that this kind of product heterogeneity does not arise, although we cannot rule out the possibility that there exists non-trivial heterogeneity in price adjustment probabilities across different retailers, and this may give rise to the convex shape. Some retailers may be more active in this market than others, and therefore change their prices more often.

The product category "LCD TVs" contains 742 different products, and the statistics shown in Figure 2 are for only one of them. We calculate the median of price durations for each of the 742 products to see how it differs across different products. The result is presented in Figure 3, which shows the cumulative distribution function of the price durations for the 742 products. The vertical axis represents the fraction of products whose price durations are shorter than the value shown on the horizontal axis. The price duration corresponding to a value of 0.5 on the vertical axis is 0.56 days on the horizontal axis, meaning that the

---

[7]Denote price duration by y and its PDF and CDF by $f(y)$ and $F(y)$, respectively. Then the hazard function $h(y)$ is related to the CDF of y as follows: $h(y) = -\frac{d}{dy}\log[1 - F(y)] = \frac{f(y)}{1-F(y)}$. If the price duration obeys a Poisson process, $h(y)$ is constant, so that the derivative of $\log[1 - F(y)]$ with respect to y is constant as well.

price duration for a representative product at the median of the CDF is 0.56 days, which is slightly longer than the median price duration of 0.34 days for the particular product used in Figure 2. More importantly, we see substantial heterogeneity in terms of price duration across different products. For example, products whose price durations are longer than 3 days account for about twenty percent of the 742 products. This kind of heterogeneity in terms of price duration is similar to the findings of previous studies on micro price stickiness, but it differs from them in that we actually see heterogeneity across individual products within a product category. The same is confirmed for other product categories such as "digital cameras" with 611 different individual products.

2.3   Price ranks

Figure 4 shows how the price rank for a retailer affects the probability that it will be clicked on by consumers for the AQUOS LC-32GH2 liquid crystal TV. Specifically, it shows, for the case that retailer i is ranked first or second, how the price differences with the most closely competing retailer affects the number of clicks. On the horizontal axis, the figure depicts the price difference between retailer i and the competing retailer for each point in time. A value of -0.1 indicates that the price offered by retailer i, ranking first, is 10 percent lower than that of the second-ranked retailer; a value of 0.1 indicates that the price offered by retailer i, in the second rank, is 10 percent higher than that of the first-ranked retailer. The vertical axis shows the share of retailer i in the total number of clicks.

Let us assume that retailer i offers the lowest price and is in the position indicated by point A. If it raises the price even only a little, it will be overtaken by a rival retailer and its number of clicks will decline. According to the figure, as a result of the price increase, the number of clicks would fall discontinuously. In fact, through only a small price increase, the number of clicks would almost halve.[8] On the other hand, if the retailer i, from the position indicated by point A, lowers the price, the number of clicks it receives will increase because

---

[8]While the figure shows the competitive relationship between the first and the second rank, the discontinuous change in the number of clicks seen here can also be observed for the 2nd and 3rd rank, the 3rd and 4th rank, etc. A similar discontinuity in the number of clicks is found by Baye et al. (2009) using data from a British price comparison site.

the price advantage vis-à-vis the second-ranked retailer will increase further, but that increase in the number of clicks will not be that great. Thus, the elasticity of demand for an increase and a decrease in price differs and in this sense the demand curve is kinked.[9]

Such a discontinuity in the demand curve implies that this online market is close to a perfectly competitive market with homogeneous products. However, as shown in the figure, retailer i still obtains about 20 percent of all clicks even when it offers the second lowest price, which is clearly inconsistent with perfect competition. To see this feature in more detail, we calculate in Figure 5 how the number of clicks changes depending on the price rank. The horizontal and vertical axes represent, respectively, price ranks and the share of clicks retailers obtain at that price rank. The figure is produced by using all price quotes for all products over the entire sample period. Figure 5 indicates that the retailer with the first rank indeed obtains many, but not all clicks; about 29 percent of clicks go to the first-ranked retailer. The second-ranked retailer still receives about 23 percent, and even the fifth-ranked retailer obtains more than 6 percent of all clicks. This can reflect heterogeneity across different retailers in terms of the various services associated with delivery and payment. In this sense, this market may still be regarded as an imperfectly competitive market with differentiated varieties.

3 Stylized Facts Regarding Price Adjustments by Competing Retailers

3.1 Frequency and size of price changes

The first issue we investigate is how the frequency of price adjustments and the size of price adjustments fluctuate as the average price changes. The upper panel of Figure 6 shows fluctuations in the average price of the AQUOS LC-32GH2 liquid crystal TV over a sample period of 230 days starting from November 1, 2006. This particular model was sold by 128 retailers during this period, although some of them were not in the market for some part of

---

[9]Kimball (1995) presents a model in which a version of kinked demand curve is the source of real rigidities. See, for example, Negishi (1979) for an early attempt to explain price rigidities by the presence of a kinked demand curve. On the other hand, Bhaskar (1988) shows that the presence of a kinked demand curve does not necessarily imply price rigidities.

the sample period due to, for example, the lack of inventory. The price shown here is the average of prices across all retailers present in the market at a particular point in time. The total number of price adjustments during this sample period was 2645, implying that a price change occurred about 11 times a day. As seen in the figure, the average price was on a downward trend throughout the sample period, but a closer inspection of the figure reveals that there were four phases, indicated by the shaded areas, during which the decline in the average price accelerated. The rapid decline in the average price during these four phases was probably associated with a substantial decline in marginal costs, such as a change in procurement prices, although we are not certain about that.

An important question concerns whether the rapid decline in the average price came from increases in the frequency of price adjustments or changes in the size of price adjustments. The middle panel presents the number of price adjustments conducted by some of the 128 retailers. The thin line represents the number of price decreases, while the thick line represents the number of price increases. We see that the number of decreases increased significantly during the four phases. For example, the number of decreases reached as high as 120 during the first phase, which is more than six times the regular level. Moreover, we see that there is a tendency that the number of decreases decays only gradually after each of the four phases of rapid decline, suggesting that the process of tâtonnement continues until prices fully stabilize. In contrast, the number of price increases does not show any significant change even during the four phases of rapid decline.

Turning to the size of price changes, which is shown in the lower panel, we see a substantial increase in the size of price decreases at the very beginning of each of the four phases of rapid decline. On the other hand, the average size of price increases is quite volatile and does not show any particular tendency during the four phases of rapid decline.

To investigate the contribution of the frequency and the size of price changes in more detail, we calculate the coefficient of correlation between the frequency of price changes and the change in the average price for each two-day period (i.e., the difference between the average price at the final second of the previous two-day period and that at the final second

Table 1: The frequency and the size of price changes for all retailers and for top ten retailers

	All Retailers	Top Ten Retailers
The number of price changes	2645	1716
The number of price decreases	2231	1602
The number of price increases	414	114
Correlation between the change in the average price and:		
the number of price decreases	-0.19	-0.47
the number of price increases	0.23	-
the size of price decreases	-0.03	0.03
the size of price increases	0.19	-

Notes: The correlation between the price change and the number of price decreases (price increases) is calculated as the coefficient of correlation between the price change during a two-day period and the number of price decreases (price increases) during that period. The correlation between the price change and the size of price decreases (increases) is calculated in a similar way. The correlation with the number of price increases and that with the size of price increases are not calculated for top ten retailers, because the number of observations is very limited.

of the current two-day period), as well as the coefficient of correlation between the size of price changes and the price change for each two-day period. The result is presented in the middle column of Table 1. This shows that the frequency of price decreases (increases) is negatively (positively) correlated with the price change, indicating higher (lower) frequency of price decreases (increases) when the average price declines rapidly. However, the correlation with the frequency of price decreases is not so large, probably reflecting the fact that the two variables are correlated not simultaneously but with some lags as we saw in Figure 6. On the other hand, the size of price decreases is uncorrelated with the price change, while the size of price increases is positively correlated with the price change.

It should be noted that the 128 retailers that sell this particular LCD TV model in this online market are not necessarily all directly competing with each other by closely monitoring each other's pricing behavior. For example, some of the retailers with a long history and a high reputation with customers may not need to compete directly with retailers who have only recently started business and thus have to offer lower prices to attract customers. In order to reflect this, we also focus on a sample of retailers that are most likely to compete with each other. Specifically, in the third column of Table 1, we calculate the average price

charged by the top ten retailers (i.e., the ten retailers offering the lowest prices) in each period and estimate the correlation with the frequency and the size of price changes. The number of price decreases conducted by the top ten retailers is 1602, which accounts for 72 percent of all price decreases conducted by all retailers present in this market. In contrast, the number of price increases conducted by the top ten retailers accounts for only 27 percent of all price increases conducted by all retailers.[10] This suggests that the top ten retailers are in keener price competition than the other retailers. More importantly, the correlation with the number of price decreases is now much higher than in the case of the average price of all retailers, suggesting that those retailers whose prices are close to the lowest one are more likely to change the frequency of price adjustments (and thus less likely to change the size of price adjustments) in their price competition, as compared to the other retailers.

3.2 Persistence in the frequency and the size of price changes

The upper panel of Figure 7 shows the estimated autocorrelations for both the size and the frequency of price changes based on the average price of all retailers. The frequency of price changes has a high positive correlation of around 0.5 with its value two days before, and this autocorrelation gradually decays until it reaches zero vis-à-vis the frequency of price changes ten days before. This implies that the expected waiting time until the next price change event is smaller (greater) if the previous price duration is shorter (longer). In contrast, the size of price adjustments has no significant correlation with its past values. We did the same exercise using the frequency and the size of price adjustments in the average price offered by the top ten retailers. The results are presented in the lower panel of Figure 7 and are quite similar to the one for all retailers, indicating that the results are robust to changes in the measure of inflation.[11]

---

[10]The average size of price decreases for the top ten retailers is about one third of that for all retailers. This indicates that the top ten retailers cut prices more often than the other retailers, but the magnitude of price cut is much smaller.

[11]Note that the different results for the size and the frequency of price changes are difficult to explain with existing models. Time dependent pricing models imply some persistence in the size of price changes because new prices spread to firms only gradually because of nominal rigidities, and no persistence in the frequency of price changes. Thus, time dependent pricing models, with or without strategic complementarities, predict results opposite to what we observe in the data. On the other hand, state-dependent pricing models imply that first-adjusters, who are far away from the desired price level, change prices by more than followers

The lack of persistence in the size of price adjustments is similar to Bils et al.'s (2009) finding using raw data of the U.S. CPI that the size of price changes is not positively correlated with its past values. In fact, they find a negative autocorrelation, rather than a positive one, both for reset price inflation (i.e., the rate of change of desired prices) and for the rate of inflation defined in the standard manner. As for persistence in the frequency of price changes, Klenow and Kryvtsov (2008) look for bunching of price changes (or price synchronization) using raw data of the U.S. CPI for 1988-2003 and report that there is little price bunching in the sense that the number of price adjustments does not fluctuate much during this period of low inflation. On the other hand, Gagnon (2009) finds evidence for the bunching of price changes during high inflation periods in Mexico. Our result looks closer to what is observed in Mexico (with high inflation) than in the U.S. (with low inflation), although neither of the two studies attempts to estimate the extent to which price bunching persists. The study most closely related to ours is Davis and Hamilton (2004), which investigates stickiness in gasoline prices for nine gasoline wholesalers by estimating an autoregressive conditional hazard model where price duration is allowed to depend on its past values. They find a positive dependence of price duration on its past values for six out of the nine firms and a negative dependence for the remaining three firms.

What does the estimated persistence in the frequency of price changes imply? As we saw in Section 2.2, the median of price durations of this product is 0.34 days. Is this number consistent with the result from Figure 7 that it takes ten days before all retailers have completed their price adjustments? To address this question, let us assume a Calvo-type setting and consider a case in which a common shock (such as a common shock to marginal costs) hits all retailers at time 0. We denote the waiting time until representative retailer i experiences its first Calvo event by τ_i and the waiting time until all of the 128 retailers have at least one Calvo event by T. The random variable T is related to τ_i as $T \equiv \max\{\tau_1, \tau_2, \ldots, \tau_{128}\}$. Note that τ_i follows an exponential distribution in the Calvo setting where price adjustment events

_____

(Golosov and Lucas's (2007) selection effect), so that the size of price adjustments is positively correlated with its past values, while implying some persistence in the frequency of price adjustments as well, because the probability of price adjustments is higher for first-adjusters than for followers. State-dependent pricing models with strategic complementarities imply even higher persistence in the size of price adjustments, as well as in the frequency of price adjustments.

occur according to a Poisson process. Making use of this fact, we calculate the expectation of T and obtain $E(T) = 1.89$.[12] That is, it takes only 1.89 days before all the retailers complete their price adjustments, which is much shorter than ten days. This simple calculation indicates that each of the 128 retailers conducts, on average, 5.3 (=10/1.89) rounds of price adjustments before all adjustments are completed.

Why do they conduct multiple rounds of adjustments? This issue is beyond the scope of this paper, but one may think of various reasons. One possibility is that shocks themselves occur only gradually; for example, shocks are common across retailers but do not affect all retailers simultaneously and instead may affect some retailers earlier than others. Alternatively, there may exist heterogeneity with some retailers responding to a shock more quickly than others. Furthermore, multiple rounds of price adjustments may arise because of imperfect knowledge about the price sensitivity of customers or about the cost structure of rivals. In this case, retailers cannot calculate a desirable price level, so that it may be optimal for them to experiment a set of different prices temporarily until they eventually reach a desirable level. Such experimentation may be the source of multiple rounds of price adjustments.

3.3 The probability of price adjustment conditional on the number of previous adjustments by competing retailers

Given the presence of persistence in the frequency of price changes, an interesting question to be asked is whether the price change by a retailer is correlated with the price changes by the other retailers. To investigate this, we estimate something similar to a hazard function. Let us suppose that retailer i changes its price at a particular point in time, and that the total number of price adjustments by *other* retailers after that point in time is n. We then calculate the probability of a price adjustment by retailer i conditional on the occurrence of the n price adjustments by the other retailers.

Figure 8 shows the estimation result. The horizontal axis represents the value of n; for

---

[12]Since τ_i follows an exponential distribution with an exponent of 0.34^{-1}, the probability that no Calvo events occur to retailer i until time t is given by $\exp(-0.34^{-1}t)$. Thus the probability that at least one of the 128 retailers does not experience any Calvo event until time t is given by $1 - [1 - \exp(-0.34^{-1}t)]^{128}$. Differentiating this with respect to t, we obtain $\frac{128}{0.34} \exp(-0.34^{-1}t)[1 - \exp(-0.34^{-1}t)]^{127}$, which is the probability that the last retailer experiences a Calvo event (and therefore price adjustments are completed for all of the 128 retailers) at time t. We use this result to calculate $E(T)$.

example, $n = 4$ means that four price adjustments by other retailers have occurred since the last price adjustment by retailer i, and the corresponding value on the vertical axis represents the conditional probability that it is retailer i that conducts the next price adjustment. This figure resembles those frequently used in previous studies, such as Alvarez et al. (2005) among others, except that the horizontal axis represents not the elapsed time but the number of price adjustments by other retailers.[13]

As seen in the figure, the conditional probability of price adjustment increases with n at least until $n = 7$. This result indicates that retailer i's decision is significantly influenced by the pricing behavior of other retailers. Note that the conditional probability starts to decline from $n = 8$ onward, which may reflect that there still remains some heterogeneity among retailers in terms of the probability of price adjustments.

Menu cost models imply that the probability of price adjustment increases with time, because the deviation of the current price level from the desired one increases as time elapses. One may think that the upward sloping part of the hazard function in Figure 8 simply reflects this property. However, as we saw in Figure 2 (b), the standard hazard function for this product, i.e., the one with the elapsed time on the horizontal axis, is actually *downward* sloping, implying that the upward sloping part of the hazard function in Figure 8 does not stem from this property.

Then the question is why we have different results depending on whether we have the elapsed time or the number of price adjustments by competing retailers on the horizontal axis. It is important to note that clustering in price adjustments in this market would contribute to creating a downward sloping hazard function with the elapsed time on the horizontal axis. However, such an effect of clustering on the shape of the hazard function is weakened by replacing the horizontal variable with n, since n is not highly correlated with the elapsed time. For example, the price change events identified by $n = 5$ may occur not only in busy periods with many price adjustments, but also in quiet periods with smaller numbers of adjustments. Therefore, the time elapsed during the five price adjustments differs substantially from one

---

[13]When estimating hazard functions, it is important to use data for a homogenous set of retailers. To do so, we focus only on retailers that are positioned at the 5th rank or above immediately after the last price adjustment.

event to another. In fact, we confirm from the data that the average length of intervals between two consecutive price adjustments by competing retailers is correlated with n only weakly.

4 State-Dependent Pricing with Strategic Complementarities

In this section, we will introduce the generalized Ss model proposed by Caballero and Engel (2007) to describe state-dependent pricing with strategic complementarities, and conduct numerical simulations with calibrated parameters to see whether we can replicate the facts found in the last section.

4.1 Setting and parameter values

Consider a setting in which each retailer reviews its price and, if necessary, adjusts it. Suppose that the opportunity of a price review arrives according to a Poisson process with a probability of $1 - \theta$. When this opportunity arrives for a retailer, it compares its current price with what Caballero and Engel (2007) refer to as the target price. The retailer changes its price if the discrepancy between the two is sufficiently large and sets a new price equal to the target price.

A key assumption concerns how the target price is determined. Here we assume that there are two types of retailers. The first type of retailers pays no attention to the prices offered by rival retailers. The target price of these retailers is equal to marginal costs, m_t, plus some margin, which is assumed to be small. On the other hand, the second type of retailers considers the prices offered by rivals in deciding their target prices. Specifically, their target price is equal to a weighted average of the average value of the prices offered by those who changed their prices in the previous period ("adjusters") and the average value of the prices offered by those who did not change their prices in the previous period ("non-adjusters"), which are denoted by P_{t-1}^A and P_{t-1}^{NA}, respectively. The fraction of the first type in the total number of adjusters in each period is assumed to be constant and given by $1 - \alpha$. Finally, we assume that a typical retailer is a combination of the two types with the weights $1 - \alpha$

and α. Then the target price of this retailer, which is denoted by P_{it}^*, is given by

$$P_{it}^* = (1 - \alpha)m_t + \alpha \left[\omega P_{t-1}^A + (1 - \omega)P_{t-1}^{NA} \right] + \epsilon_{it} \qquad (1)$$

where ω is a parameter between 0 and 1, ϵ_{it} is a disturbance term, and P_{it}^*, m_t, P_{t-1}^A, and P_{t-1}^{NA} are all in logarithm.

The probability that retailer i changes its price conditional on that it is allowed to review its price is denoted by Λ and assumed to depend on x_{it}, which is defined by $x_{it} \equiv P_{it-1} - P_{it}^*$. The function $\Lambda(x_{it})$ is what Caballero and Engel (1993a) refer to as the "adjustment hazard function." This is a useful tool to discriminate between state-dependent and time-dependent pricing. If the probability of price adjustment depends upon a state variable, x, it is state-dependent pricing, and if not, it is time-dependent pricing. We make two assumptions about the shape of the adjustment hazard function. First, the probability of price adjustment becomes higher as the actual price deviates more, positively or negatively, from the target level, so that $\Lambda'(x) > 0$ for $x > 0$ and $\Lambda'(x) < 0$ for $x < 0$. Caballero and Engel (1993b) call this the increasing hazard property. Second, the adjustment hazard function is assumed to be symmetric.

Calibrated parameters are set as follows. We assume that the number of retailers is ten and that the length of each time step is 3.6 minutes, or 40 steps=1 day. As for the probability of price review, we assume that each retailer reviews its price, on average, 0.4 times a day, which implies $1 - \theta = 0.01$. This is based on the interviews we conducted with major players in the Kakaku.com market. As for marginal costs m_t, we assume that the decline in marginal costs occurs according to a Poisson process, and that the probability of the decline is 0.002 per time step, implying that a decline in marginal costs occurs, on average, 30 times a year. The size of the decline in marginal costs is assumed to be 1 percent of the price level. Combining these two, marginal costs m_t and therefore the price level decline, on average, by 30 percent per year, which is consistent with what is observed in the data.

Following Caballero and Engel (2006), the adjustment hazard function is assumed to be

of quadratic form and can be represented by:

$$\Lambda(x) = \begin{cases} 1 & \text{if} & x < -\lambda_0 \\ (x/\lambda_0)^2 & \text{if} & -\lambda_0 \le x \le \lambda_0 \\ 1 & \text{if} & \lambda_0 < x \end{cases} \tag{2}$$

where λ_0 is a positive parameter. The value of λ_0 is assumed to be 0.05, implying that the probability of adjustment is equal to unity if the deviation of the current price from the target level is above 5 percent, while it is less than unity if the deviation is less than 5 percent. Finally, the parameters appearing in equation (1) are assumed to be $\alpha = 0.9$ and $\omega = 0$. The value of α is based on the empirical autocorrelation in the frequency of changes in the lowest price.[14]

4.2 Simulation results

The simulation results are presented in Figure 9. The left panel shows autocorrelations for the frequency and the size of price changes. The results clearly show that there is a positive autocorrelation both in the frequency and the size of price adjustments, although the autocorrelation is slightly larger and longer for the frequency of adjustments than for the size of adjustments. Note that such persistence in the frequency and the size of price adjustments stems mainly from strategic interactions among retailers due to the presence of strategic complementarities described by equation (1). Comparing these results with the empirical ones presented in Figure 7, we see no difference as far as the frequency of price adjustments is concerned. However, there is an important difference for the size of price adjustments in that the empirical autocorrelations are almost zero. In the Caballero-Engel model, the state variable x determines the size of adjustments, but it also determines the likelihood of adjustments through the adjustment hazard function $\Lambda(x)$. Given the increasing hazard property of this function, a higher (lower) probability of price adjustment tends to be associated with greater (smaller) size of adjustment. This feature is seen in the simulation result but not in the empirical one. The empirical result may suggest that the size of adjustments is determined in a way different from the one described by the Caballero-Engel model.

---

[14]To test the robustness of our results, we also conducted simulations with slightly smaller values of α ($\alpha = 0.8$ and 0.7), as well as different values of ω. The results are similar to the ones reported in the text.

Turning to the right panel of Figure 9, this shows the probability of a price adjustment by retailer i conditional on the occurrence of n price adjustments by other retailers. Comparing this with the empirical result presented in Figure 8, the model successfully replicates the pattern that the conditional probability increases with n, although the simulation result does not show the property that the hazard function is downward sloping for large values of n, as we saw in the data. This difference may be accounted for by heterogeneity across retailers in terms of the probability of price adjustment, which is absent in the model.

5   Conclusion

In this paper, we have investigated retailers' price setting behavior using a unique dataset containing by-the-second records of prices offered by competing retailers on a major Japanese price comparison website. We find that, when the average price of a product across retailers falls rapidly, the frequency of price adjustments increases, and the size of price adjustments becomes larger. This suggests that pricing behavior of competing retailers is characterized by state-dependent pricing, rather than time-dependent pricing. We also find that there is positive autocorrelation in the frequency of price adjustments, implying that there tends to be clustering where once a price adjustment occurs, such adjustments occur in succession. Our estimate of the length of such clustering is about ten days, which is about five times as long as implied by the Bils-Klenow type estimate of the length of price spells. This implies that each retailer goes through, on average, five rounds of price adjustments before the entire process of adjustments is completed.

Can we carry over these results to the world outside internet markets? Probably not, because pricing behavior in online markets may be quite different from that in offline markets. Does there exist a similar clustering in price adjustments outside internet markets? And if so, is it large enough to account for the differences in price stickiness at the micro and macro levels? These are the questions to be addressed in future work.

References

[1] Alvarez, L. J., P. Burriel, and I. Hernando (2005). "Do Decreasing Hazard Functions for Price Changes Make Sense?," Working Paper 461, European Central Bank.

[2] Ball, L., and D. Romer (1990), "Real Rigidities and the Non-Neutrality of Money," *Review of Economic Studies* 57(2), 183-204.

[3] Bhaskar, V. (1988), "The Kinked Demand Curve: A Game-Theoretic Approach," *International Journal of Industrial Organization* 6, 373-384.

[4] Baye, M. R., J. R. J. Gatti, P. Kattuman, and J. Morgan (2009), "Clicks, Discontinuities, and Firm Demand Online," May 2009.
http://www.nash-equilibrium.com/baye/Shoppers.pdf.

[5] Bils, M., and P. J. Klenow (2004), "Some Evidence on the Importance of Sticky Prices," *Journal of Political Economy* 112(5), 947-985.

[6] Bils, M., P. J. Klenow, and B. A. Malin (2009), "Reset Price Inflation and the Impact of Monetary Policy Shocks," NBER Working Paper 14787.

[7] Caballero, R. J., and E. M.R.A. Engel (1993a), "Microeconomic Rigidities and Aggregate Price Dynamics," *European Economic Review* 37(4), 697-717.

[8] Caballero, R. J., and E. M.R.A. Engel (1993b), "Microeconomic Adjustment Hazards and Aggregate Dynamics," *Quarterly Journal of Economics* 108(2), 359-383.

[9] Caballero, R. J., and E. M.R.A. Engel (2006), "Price Stickiness in Ss Models: Basic Properties," MIT and Yale.

[10] Caballero, R. J., and E. M.R.A. Engel (2007), "Price Stickiness in Ss Models: New Interpretations of Old Results," *Journal of Monetary Economics* 54 (Supplement 1), 100-121.

[11] Calvo, G. (1983), "Staggered Prices in a Utility-Maximizing Framework," *Journal of Monetary Economics* 12(3), 383-398.

[12] Cooper R., and J. Haltiwanger (1996), "Evidence on Macroeconomic Complementarities," *Review of Economics and Statistics* 78(1), 78-93

[13] Davis, M. C., and J. D. Hamilton (2004), "Why Are Prices Sticky? The Dynamics of Wholesale Gasoline Prices," *Journal of Money, Credit and Banking* 36, 17-37.

[14] Dhyne, E., L. J. Alvarez, H. L. Bihan, G. Veronese, D. Dias, J. Hoffmann, N. Jonker, P. Lunnemann, F. Rumler, and J. Vilmunen (2006), "Price Setting in the Euro Area and the United States: Some Facts From Individual Consumer Price Data," *Journal of Economic Perspectives* 20(2), 171-192.

[15] Gagnon, Etienne (2009), "Price Setting during Low and High Inflation: Evidence from Mexico," *Quarterly Journal of Economics* 124, 1221-1263.

[16] Golosov, M., and R. E. Lucas (2007). "Menu Costs and Phillips Curves," *Journal of Political Economy* 115(2), 171-199.

[17] Gopinath, G. and O. Itskhoki, "Frequency of Price-Adjustment and Passthrough," *Quarterly Journal of Economics*, forthcoming.

[18] Higo, M., and Y. Saita (2007), "Price Setting in Japan: Evidence from CPI Micro Data," *Bank of Japan Working Paper Series* 07-E-20, Bank of Japan.

[19] Kimball, M. (1995), "The Quantitative Analytics of the Basic Neomonetarist Model," *Journal of Money, Credit and Banking* 27(4), 1241-1277.

[20] Klenow, P. J., and O. Kryvtsov (2008), "State-Dependent or Time-Dependent Pricing: Does it Matter for Recent U.S. Inflation?" *Quarterly Journal of Economics* 123(3), 863-904.

[21] Nakamura, E., and J. Steinsson (2008), "Five Facts about Prices: A Reevaluation of Menu Cost Models," *Quarterly Journal of Economics* 123(4), 1415-1464.

[22] Negishi, T. (1979), *Microeconomic Foundations of Keynesian Macroeconomics*, New York: North-Holland.
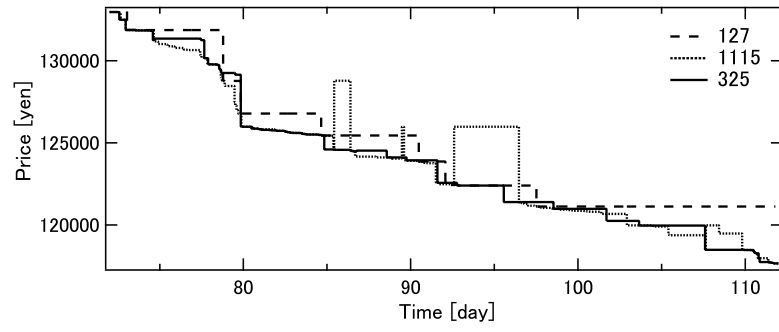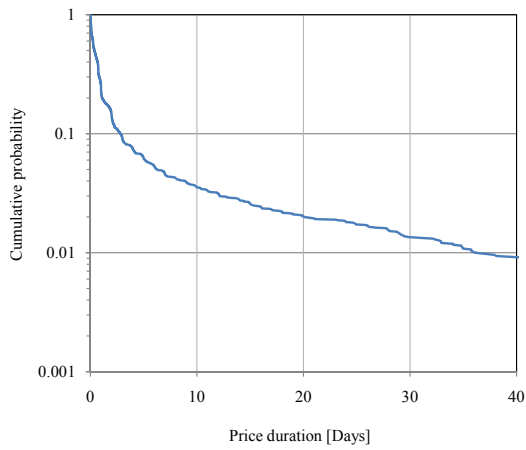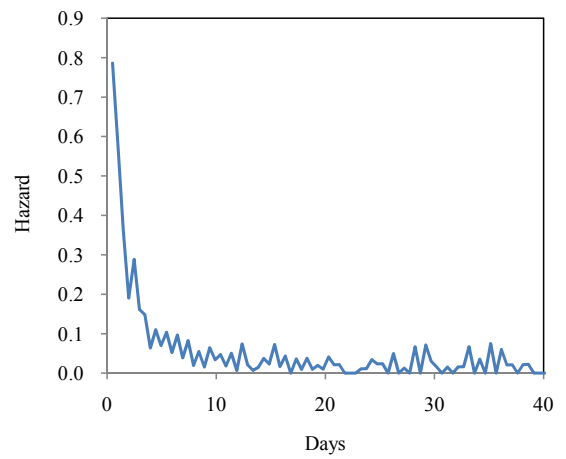
Figure 1: Prices of an LCD TV offered by three competing retailers

(a) Cumulative distribution function of the price duration

(b) Hazard function

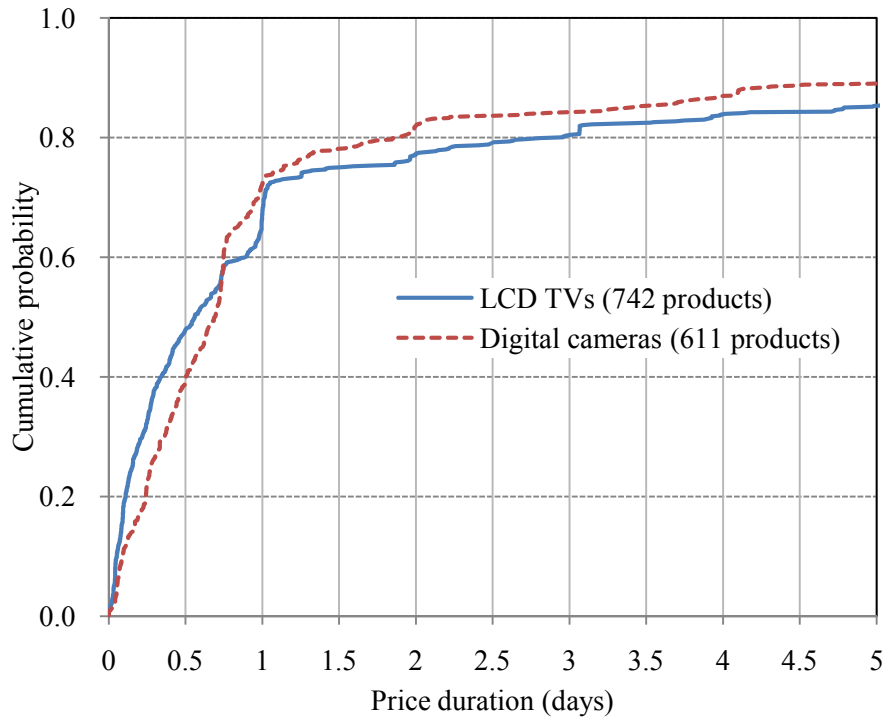Figure 2: Price duration for an LCD TV

23

Figure 3: Median price duration by product

Notes: The median of price durations is calculated for each of the 742 products in the product category "LCD TVs", as well as for each of the 611 products in the product category "Digital cameras". For each of the two product categories, the vertical axis represents the fraction of products whose price durations, measured by the median, are shorter than the value shown on the horizontal axis.
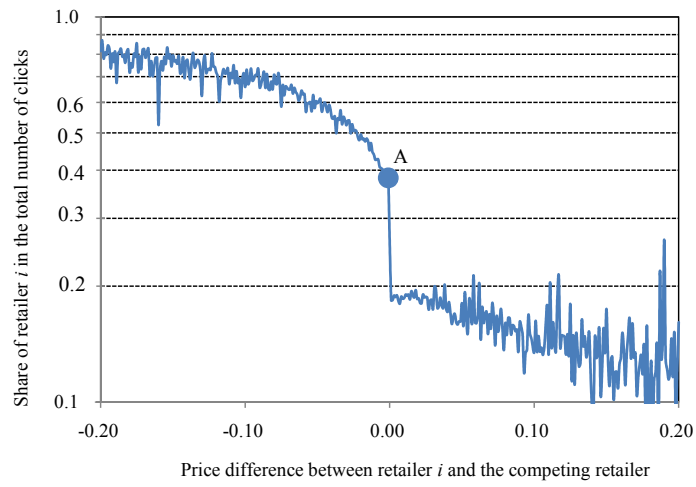
Figure 4: Relative price and the share in the number of clicks

Notes: The horizontal axis represents the price difference for an LCD TV between retailer i and its most closely competing retailer. A value of -0.1 on the horizontal axis indicates that the price offered by retailer i is 10 percent lower than that of the competitor. The vertical axis represents the share of retailer i in the total number of clicks.
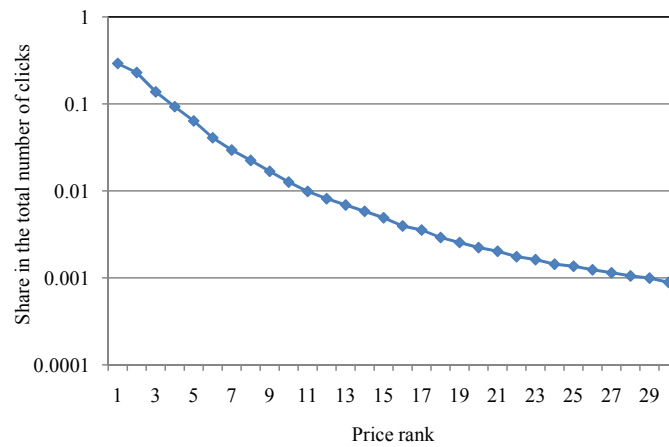
Figure 5: Price rank and the share in the number of clicks

Notes: The horizontal axis represents price rank of a retailer and the vertical axis represents the share of clicks the retailer obtains at that rank.
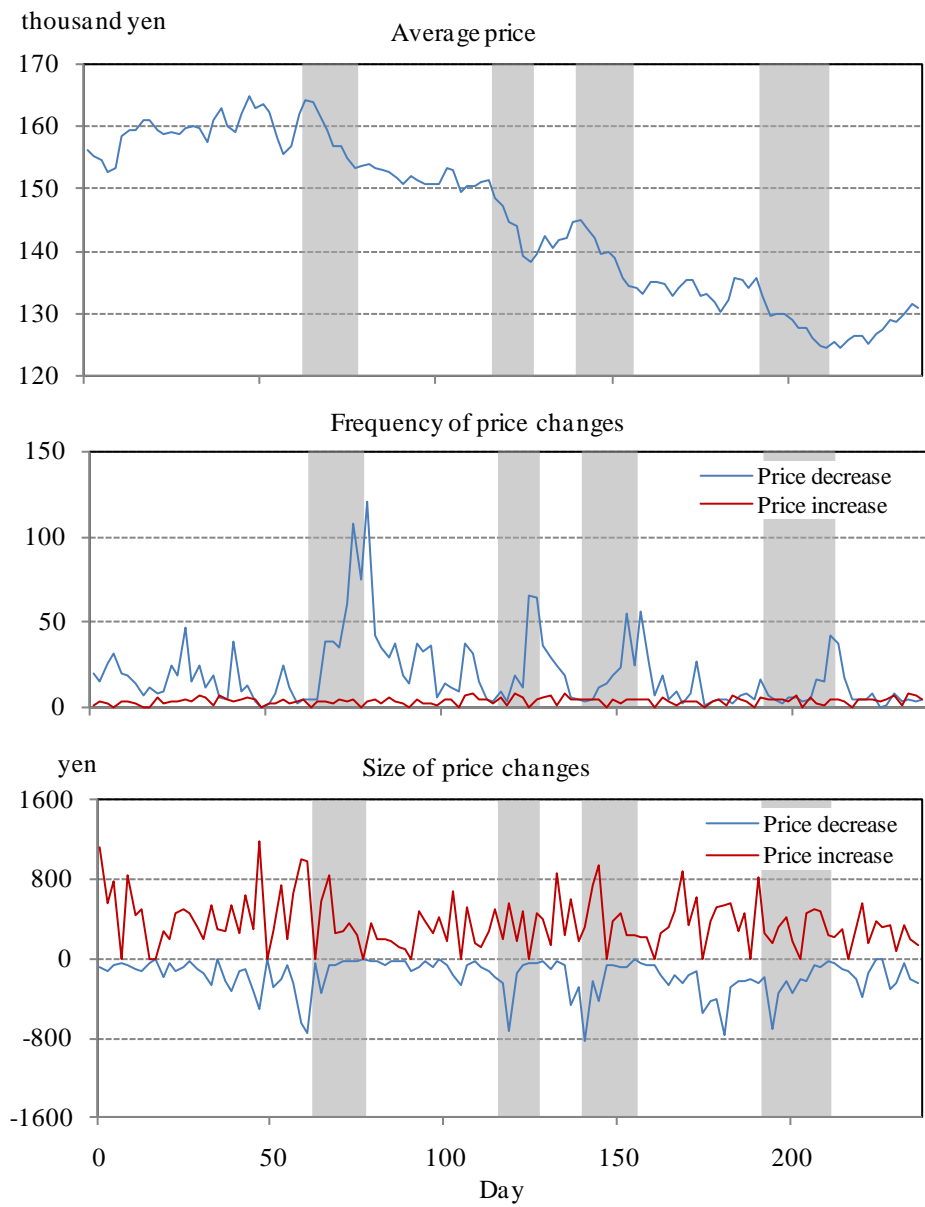
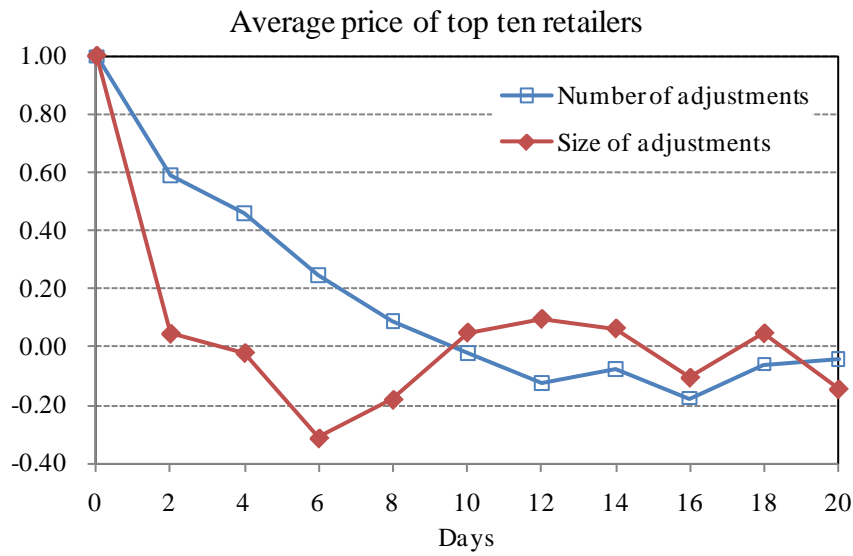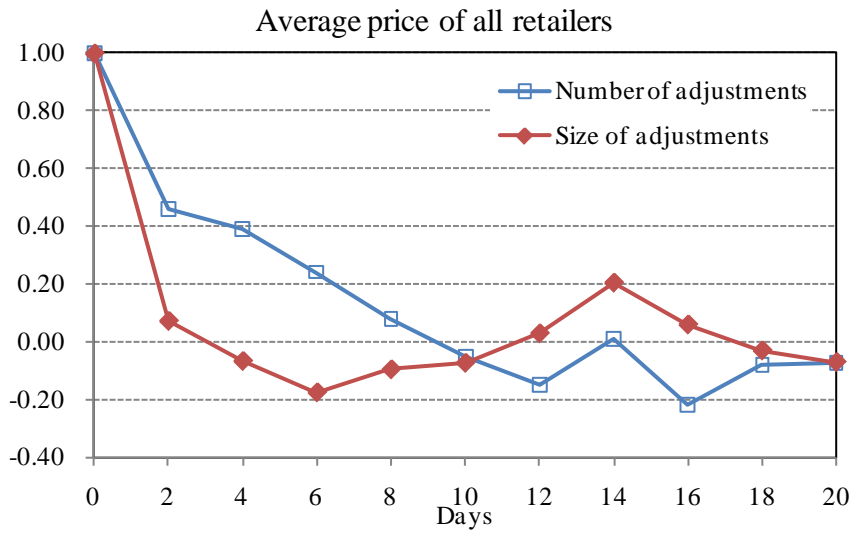Figure 6: Fluctuations in the average price of an LCD TV

Figure 7: Autocorrelation functions of the frequency and the size of price changes
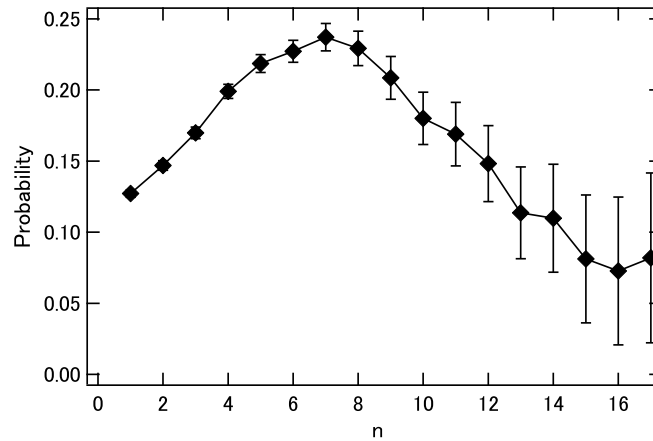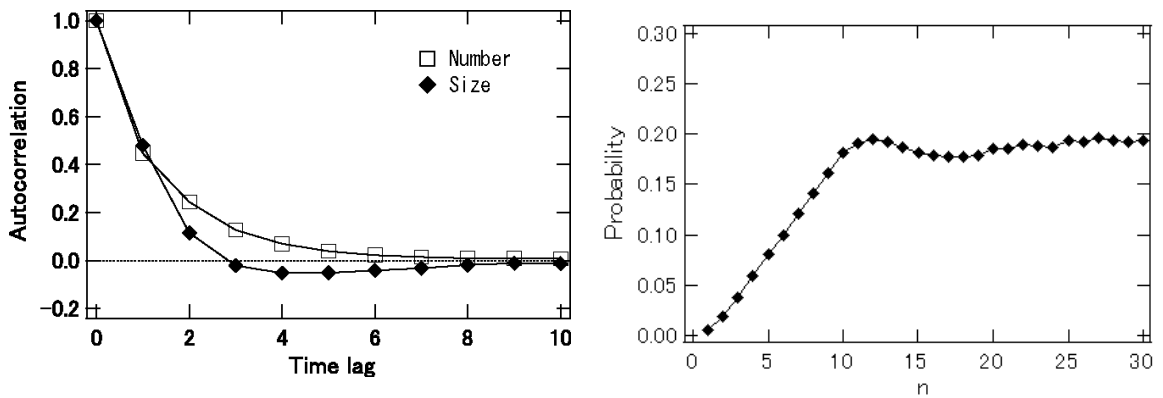
Figure 8: Probability of price adjustment conditional on the number of adjustments by rivals

Notes: The horizontal axis represents the number of price adjustments by its rivals since the last price adjustment by retailer i, and the vertical axis represents the conditional probability that it is retailer i that conducts the next price adjustment.

(a) Autocorrelations in the size and the frequency of price adjustments

(b) Probability of price change conditional on the number of changes by rivals

Figure 9: Simulation results