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

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

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## Abstract

We investigate retailers' price setting behavior, and in particular strategic interaction between retailers, using a unique dataset containing by-the-second records of prices offered by 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 is high, while the *size* of adjustments remains largely unchanged. Second, we find a positive autocorrelation in the frequency of price adjustments, implying that there tends to be a clustering where once a price adjustment occurs, such 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, especially when prices fall rapidly, and that strategic complementarities play an important role when retailers decide to adjust (or not to adjust) their prices.

*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 Bils and Klenow's (2004) seminal study, 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

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finding of such studies is that price adjustment events occur quite frequently. For example, 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 adopted in these studies is an indicator of price stickiness at the micro level. When comparing the price stickiness at the micro level suggested by this frequency measure with the price stickiness observed at the macro level, the estimated micro stickiness is clearly too low. Assuming that the measurements of both micro and macro stickiness are correct, a possible explanation for the discrepancy between the two is the existence of some sort of correlation in price adjustments across firms at the micro level. This idea, labeled “real rigidities” or “strategic complementarities” in price setting, has been advocated by Ball and Romer (1990), Kimball (1995), and others. For example, 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 may be influenced by other firms that do not adjust prices, therefore keeping the extent of the price adjustment small. Given the fraction of adjusters is 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 extent to which firms’ pricing behaviors are correlated. To do so, what is important is to collect price data of competing firms and retailers, that is, price data for individual firms and retailers whose pricing behaviors are potentially correlated with each other. Unfortunately, such data are seldom 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 the authors are aware, there exists no comprehensive dataset comprising prices

for competing retailers. For example, Saito and Watanabe (2009) use a dataset consisting of prices collected from about 400 retailers, but those retailers do not necessarily compete in the same area, and the dataset therefore is not useful for examining strategic complementarities.

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 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, with intraday observation. 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 exactly whether comovements in prices offered by different retailers come from strategic interaction between them or common shocks. In this paper, given these features of the dataset, we will focus on persistence in price adjustments conducted by competing retailers as a way to learn about the presence and the extent of strategic complementarities in price setting.

Time-dependent pricing models with strategic complementarities, including Kimball (1995), imply that multiple rounds of price adjustments, in which the size of each adjustment is smaller, emerge due to the presence of strategic complementarities. The probability of price

adjustments is exogenously given in those models, so that the presence of multiple rounds of price adjustments immediately imply that it takes longer until the entire process of price adjustments is completed. On the other hand, state-dependent pricing models imply that the number of price adjustments per a period increases due to strategic complementarities; namely, “temporal agglomeration” or clustering in price adjustments emerges.<sup>1/2</sup> In other words, the two types of models imply that both of the intensive margin (the size of price adjustments) and the extensive margin (the frequency of price adjustments) are persistent in the sense that they are correlated with their own past values. Empirical evidences on the first theoretical prediction are mixed. Specifically, Bils et al. (2009) investigate this prediction by employing the source data of U.S. CPI, failing to find a positive autocorrelation in the size of price adjustments.<sup>3</sup> In contrast, Gopinath and Itskhoki (2009) find that exchange rate changes pass-through into import prices only gradually, interpreting this fact as evidence for multiple rounds of price adjustments due to strategic complementarities. Turning to the second theoretical prediction, there does not exist any empirical papers that directly investigate this as far as the authors are aware, partly due to the absence of datasets that contain information regarding pricing behavior of competing firms.<sup>4</sup> In this paper we will examine persistence both in the intensive and extensive margins 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 is high, while the size of price adjustments does not change much. On the other hand, the size of price

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<sup>1</sup>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 adjustment by one firm and price adjustments by rival firms.

<sup>2</sup>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 survey on empirical studies that look for clustering in various economic activities, like machine replacement, investment and so on, as evidence for strategic complementarities.

<sup>3</sup>More precisely, what they did was to estimate “reset price inflation” (i.e. the rate of change of desired prices) and to evaluate its persistence in addition to the persistence in the rate of inflation defined in the standard way. They fail to find a positive autocorrelation in both of the two inflation variables.

<sup>4</sup>An indirect evidence is provided by Klenow and Kryvtsov (2008), which look for bunching of price changes (or price synchronization) using the source data of U.S. CPI in 1988-2003, finding that there is little price bunching in the sense that the number of price adjustments do not fluctuate much at least during this period with low inflation. They did not examine persistence in the number of price adjustments.

adjustments plays a more important role than the frequency of price adjustments in periods when the average price changes only gradually. This result suggests that pricing behavior of competing retailers is characterized by state-dependent pricing, rather than time-dependent pricing, and that large changes in prices are caused by fluctuations in the frequency of price adjustments while small changes are caused by fluctuations in the size of price adjustments.

Second, we find a positive and significant autocorrelation in the frequency of price adjustments, implying that there tends to be a clustering where once a price adjustment occurs, such adjustments occur in succession. In contrast, we fail to find a positive autocorrelation in the size of price adjustment. The lack of persistence in the size of price adjustment, which is similar to what Bils et al. (2009) find using the source data of CPI, rejects 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 second and third findings suggest the presence of strategic complementarities in price setting, and that the frequency of price changes plays a much more important role than the size of price changes in such strategic complementarities in price setting.

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 then examine the characteristics of price changes using autocorrelations and hazard functions. 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 (and if so, how much), whether they accept credit card payment, whether they accept cash on delivery, the address of the distribution center, 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 selling retailer, where they go through the retailer’s sales procedure and finally purchase the product. Each retailer pays fees to Kakaku.com corresponding to the number of customers sent from the Kakaku.com website to that of the retailer, which is how Kakaku.com, Inc. generates its income. Kakaku.com, Inc. does not collect any fees directly from consumers.

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. Each retailer conducts such monitoring activity with regard to all the products it offers.

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. At which price retailers offered a product may be considered to be an indication of the supply-side situation of the product, while which shop consumers clicked on represents the demand side.<sup>5</sup>

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 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. And when they occur, price adjustments are discontinuous in the sense 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

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<sup>5</sup>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.



data or scanner data.<sup>6</sup> Second, the three retailers do not adjust prices at the same time but instead each adjust 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

Studies since [Bils and Klenow \(2004\)](#) using micro price data typically employ the frequency of price adjustments as a measure for price stickiness. [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 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 ( $=1/1.93$ ), although the probability of price adjustment within 24 hours since the last price change is 0.750. If price adjustment events occur according to a Poisson process, price duration follows an exponential distribution. Because the vertical axis here is shown in logarithmic scale, if the price duration

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<sup>6</sup>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.

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, suggesting that the price duration does not follow an exponential distribution.

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,<sup>7</sup> shows that the same is the case here. However, previous studies measure hazard functions using pooled data for several products, and it has been pointed out that it is possible that the downward sloping hazard function may be the result of heterogeneity in price adjustment probability across different products. In contrast, the price spells used in Figure 2 (b) is collected only from one product, so that this kind of problem 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.

The product category “LCD TV” contains 742 different products, one of which is used in calculating statistics shown in Figure 2. We now 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 value of price duration corresponding to 0.5 on the vertical axis is 0.48 days, indicating that the typical product in this product category has a price duration slightly longer than the one for the particular product used in Figure 2. More importantly, we see substantial heterogeneity in terms of price duration across different products. For example, the 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 the price duration (or in terms of the frequency of price changes) is similar to the findings by

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<sup>7</sup>Denote price duration by  $y$  and its PDF and CDF by  $f(y)$  and  $F(y)$ , respectively. Then, a 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.

previous studies on price stickiness using micro price data, but it differs from them in that we actually see heterogeneity across individual products within a product category. The same thing is confirmed for other product categories, like “digital camera” with 611 products.

### 2.3 Price ranks

In the online market provided by Kakaku.com, the price rank has an important role. To illustrate this, Figure 4 shows how the price rank for each 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 price differences with competing retailers affect the number of clicks. On the horizontal axis, the figure depicts the price difference between retailer  $i$  and competing retailers for each point in time. For example, 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 the 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.<sup>8</sup> On the other hand, if the retailer  $i$ , from the position indicated by the point A, lowers the price, the number of clicks it receives will increase because the price advantage vis-à-vis the second-ranked retailer will expand 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.<sup>9</sup>

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<sup>8</sup>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.

<sup>9</sup>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 kinked demand curve. Bhaskar (1988) shows that the presence of kinked demand curve does not necessarily imply price rigidities.

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 price ranks. The horizontal and vertical axes represent, respectively, price ranks and the fraction 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 clicks, but not necessarily all clicks; that is, about 29 percent goes to the first-ranked retailer but the remaining 71 percent goes to the other retailers. For example, the second-ranked retailer obtains about 23 percent, and even the fifth-ranked retailer obtains more than 6 percent of all clicks. This can be interpreted as reflecting heterogeneity across different retailers in terms of various services associated with delivery and payment (like delivery time, payment instruments, and so on). In this sense, we may still regard this market as an imperfectly competitive market with differentiated varieties of a product, although it differs from a pure world of monopolistic competition with products being physically differentiated.

### **3 Stylized Facts Regarding Price Adjustment by Competing Retailers**

#### **3.1 Intensive versus extensive margins**

In this section, we look at various properties of price adjustment by competing retailers. The first issue we will investigate is how the frequency of price adjustments (the extensive margin) and the size of price adjustments (the intensive margin) fluctuate as prices change. 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 the sample period due to, for example, the lack of inventories. 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 5116, implying that it occurred about 22 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 during which the decline in the average price accelerated, each of which is shown by the shaded area. 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 quite sure about that without any information on marginal costs.

An important question concerns whether the rapid decline in the average price came from increases in the frequency of price adjustments (the extensive margin) or changes in the size of price adjustments (the intensive margin). The middle and lower panels of the figure show the two margins, respectively. Specifically, the middle panel presents the number of adjustments for each two-day period, while the lower panel shows the average size of adjustments for each two-day period. As can be clearly seen in the middle panel, the number of adjustments increased significantly during the four phases. For example, the number of adjustments reached as high as 140 during the first phase, which is more than five times the regular level. Turning to the intensive margin, the lower panel shows that the average size of adjustments tend to become slightly larger (i.e., larger declines) during the four phases.

To investigate the contribution of the extensive and the intensive margin in more detail, we calculate the coefficient of correlation between the extensive margin and the price change for each two-day period (i.e., the difference between the average price at the final second of the previous two-day period and at the final second of the current two-day period), as well as the coefficient of correlation between the intensive margin and the price change for each two-day period. The result is presented in the upper panel of Table 1. This shows that the intensive margin is highly correlated with the price change, although the correlation is a little smaller in periods when the price decline exceeds 1,000 yen. On the other hand, the extensive margin is highly correlated with the price change in periods when the price decline exceeds 1,000 yen, which is consistent with what we saw in Figure 6. However, the extensive margin

Table 1: Correlations between the price changes and the intensive and extensive margins

<i>Average Price of All Retailers</i>		
Price changes [in yen]	Correlations between the price change and:	
	Extensive margin	Intensive margin
$\Delta P < -1000$	-0.214	0.405
$-1000 \leq \Delta P < 0$	-0.086	0.633
$0 \leq \Delta P$	0.126	0.770
<i>Average Price of Top Ten Retailers</i>		
Price changes [in yen]	Correlations between the price change and:	
	Extensive margin	Intensive margin
$\Delta P < -1000$	-0.360	0.319
$-1000 \leq \Delta P < 0$	-0.309	0.280
$0 \leq \Delta P$	0.120	0.765
<i>Lowest Price</i>		
Price changes [in yen]	Correlations between the price change and:	
	Extensive margin	Intensive margin
$\Delta P < -1000$	-0.619	0.138
$-1000 \leq \Delta P < 0$	-0.332	0.439
$0 \leq \Delta P$	0.124	0.787

Note: The correlation between price changes and the extensive margin is calculated as the coefficient of correlation between price changes during two-day intervals and the frequency of price changes during those intervals when those price changes fall within the range indicated in the left-hand column. The correlation between price changes and the intensive margin is calculated in a similar way.

is not significantly correlated with the price change during those quiet periods without large price fluctuations.<sup>10</sup>

It should be noted that all of the 128 retailers that sell this particular model of LCD TV in this online market are not necessarily competing with each other by closely monitoring each other's pricing behavior. For example, some of the retailers with long history and high reputation from customers may not need to compete with those retailers who have recently started business and thus have to offer low prices to attract customers. Given this understanding, we attempt to obtain the sample of retailers that are more likely to compete with each other. Specifically, in the middle panel of Table 1, we calculate the average price

<sup>10</sup>Gagnon (2009) finds using the source data of Mexican CPI that the correlation between inflation and the extensive margin is low in high inflation periods, while it is low in low inflation periods. Our finding that the extensive margin is more highly correlated with inflation in periods when the average price declines sharply is similar to Gagnon's finding in the sense that the extensive margin plays a more important role when the average price exhibit large fluctuations.

among the top ten retailers (i.e. those retailers who offer the lowest ten prices) in each period, and estimate the correlation with the corresponding intensive and extensive margins. Furthermore, in the lower panel, we focus on the top retailer (i.e. the retailer who offers the lowest price) in each period, and conduct a similar calculation. We see that, in periods when the average price of top ten retailers declines more than 1,000 yen, the correlation with the extensive margin is 0.360, which is higher compared to the case of all retailers (0.214), while the correlation with the intensive margin is slightly lower. We see this tendency more clearly in the case of the lowest price; that is, the correlation with the extensive margin in periods when the lowest price declines more than 1,000 yen is much higher (0.619) compared to the other two cases, and even higher than the one for the extensive margin (0.138), indicating that the extensive margin plays a dominantly important role in those periods. These results indicate that, in periods when prices decline sharply, retailers that offer prices close to the lowest one change prices very frequently, and this is the source of high correlation between inflation and the extensive margin in those periods.

In sum, the above results indicate that the frequency of price adjustments changes over time depending on the environment surrounding retailers, thus clearly rejecting the idea that price adjustment events occur according to a Poisson process. The results also indicate that the extensive margin plays a more important role than the intensive margin on days with large price changes.

### **3.2 Persistence in intensive and extensive margins**

The upper panel of Figure 7 shows the estimated autocorrelations for both the intensive and the extensive margin using the corresponding variables in the average price of all retailers. The extensive margin (the frequency of price adjustments) 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 extensive margin ten days before. This implies that expected waiting time to the next price change event is smaller (greater) if the previous price duration is shorter (longer). In contrast, the intensive margin (the size of price adjustments) has no significant correlation with its past values. We did the same exercise using the corresponding

intensive and extensive margins in the average price of top ten retailers, and those in the lowest price. The results presented in the middle and lower panels of Figure 7 are quite similar to the one for all retailers, indicating that the results are robust to changes in the measure of inflation.<sup>11</sup>

The lack of persistence in the intensive margin is similar to the finding by *Bils et al.* (2009), which employs the source data of U.S. CPI to find that the size of price changes is not positively correlated with its past values.<sup>12</sup> As for the persistence in the extensive margin, *Klenow and Kryvtsov* (2008) look for bunching of price changes (or price synchronization) using the source data of U.S. CPI in 1988-2003, reporting that there is little price bunching in the sense that the number of price adjustments do not fluctuate much during this period with low inflation. On the other hand, *Gagnon* (2009) finds evidence for 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. A 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, while a negative dependence for the remaining three firms.

What does the estimated persistence in the extensive margin 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

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<sup>11</sup>Note that the different results for the intensive and extensive margins are hard to explain by the existing models. Time dependent pricing models imply some persistence in the intensive margin because new prices spread to firms only gradually because of nominal rigidities, while no persistence in the extensive margin. Thus time dependent pricing models, with or without strategic complementarities, predict results opposite to what we have observed 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 (because of *Golosov and Lucas* (2007)'s selection effect), so that the intensive margin is positively correlated with its past values, while implying some persistence in the extensive margin 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 intensive margin, as well as in the extensive margin. This issue will be discussed again in Section 4 through simulation analysis.

<sup>12</sup>In fact, they find that the size of price changes is negatively correlated with its past values. They report a negative autocorrelation both for reset price inflation (i.e., the rate of change of desired prices) and for the rate of inflation defined in the standard way.



the result that it takes ten days before every retailer completes price adjustment? To address this question, let us assume a Calvo-type setting and think about a case in which a common shock (such as a common shock to marginal costs) hits each retailer at time 0. We denote the waiting time until the first Calvo event occurs to retailer  $i$  by  $\tau_i$ , 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  $\tau_i$  as  $T \equiv \max\{\tau_1, \tau_2, \dots, \tau_{128}\}$ . Note that  $\tau_i$  follows an exponential distribution in the Calvo setting where price adjustment events occur according to a Poisson process. Making use of this fact, we calculate the expectation of  $T$  to obtain  $E(T) = 1.89$ .<sup>13</sup> That is, it takes only 1.89 days before every retailer completes price adjustment, which is much shorter than ten days. This simple calculation indicates that each of the 128 retailers experiences, on average, 5.3 (=10/1.89) rounds of price adjustments before all adjustments are completed.

Why do they conduct multiple rounds of adjustments? One possibility is that shocks themselves occur only gradually; for example, shocks are common across retailers but not simultaneously occur to each retailer, and they may come to some retailers earlier than the other. Alternatively, strategic complementarities may play an important role in price setting when retailers decide to adjust (or not to adjust) their prices.<sup>14</sup>

### 3.3 Probability of price adjustment conditional on the number of previous adjustments by competing retailers

To learn more about causes behind the positive autocorrelation in the extensive margin, we estimate something similar to the hazard function. 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

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<sup>13</sup>Since  $\tau_i$  follows an exponential distribution with the exponent of  $0.34^{-1}$ , the probability that no Calvo events occur in 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 get  $\frac{128}{0.34} \exp(-0.34^{-1}t)[1 - \exp(-0.34^{-1}t)]^{127}$ , which is the probability that a final 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  $E(T)$ .

<sup>14</sup>Multiple rounds of price adjustments may arise because of the 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 an experimentation may be the source of multiple rounds of price adjustments.

$i$  conditional on the occurrence of the  $n$  price adjustments by the other retailers. Without strategic complementarities in price setting, retailer  $i$  would not be affected by the  $n$  price adjustments implemented by the other retailers, so that the probability of a price adjustment by retailer  $i$  does not depend on  $n$  at all. However, with strategic complementarities, a larger  $n$  means that the price offered by retailer  $i$  is obsolete, and is far away from the current price levels offered by rivals. Therefore, retailer  $i$  has a stronger incentive to adjust its price, so that the conditional probability increases with  $n$ .

Figure 8 shows the estimation result. The horizontal axis represents the value of  $n$ ; for example,  $n = 4$  means that four price adjustments by other retailers occur after 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. As often pointed out in those studies, 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.

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 looks quite similar to the downward-sloping hazard functions repeatedly reported in previous studies on price stickiness. The declining conditional probability could be interpreted as reflecting the fact that there still remains some heterogeneity among retailers in terms of the probability of price adjustments.

Let us make two remarks related to this result. First, menu cost models imply that the probability of price adjustments increases with time, because the deviation of the current price level from the desired one increases as time elapses, therefore firms have more incentive to adjust prices. Note that this property has nothing to do with strategic complementarities.

One may think that the upward sloping hazard curve in Figure 8 simply reflects this property. In fact, 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 curve observed in Figure 8 does not stem from this property.

Given this understanding, a more important question to be addressed 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. As we saw in Figure 7, there is clustering in price adjustments, where price spells with short (long) durations tend to be followed by those with short (long) durations. Other things being equal, such clustering itself would create a downward sloping hazard function with the elapsed time on the horizontal axis, and this explains why the estimated hazard function in Figure 2 (b) is downward sloping. However, such an effect of clustering on the shape of a hazard function is eliminated at least partially by replacing the horizontal variable to the number of price adjustments by competing retailers. For example, the price change events identified by  $n = 5$  may occur not only in busy periods with many adjustments, but also in quiet periods with smaller numbers of adjustments. Therefore, the time elapsed during five price adjustments differs substantially among the price change events identified by  $n = 5$ , implying that the effect of clustering is eliminated to some extent.<sup>15</sup>

The second remark is related to the question whether the result in Figure 8 can be accounted for by the presence of common shocks that are different in timing across retailers. Let us start by considering a benchmark case in which a common shock occurs to each retailer simultaneously. In response to this shock, the probability of price adjustment would increase for each retailer, but the extent it increases may be different across retailers. Those retailers with very high probabilities change their prices immediately after the shock, while those with not so high probabilities would not change prices so quickly. This implies that the retailers

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<sup>15</sup>However, the effect of clustering is not eliminated completely. We see from the data that the average length of intervals between two consecutive price adjustments by competing retailers tends to increase with  $n$ . For example, the price change events identified by  $n = 6$  tend to occur in periods with longer intervals than the events identified by  $n = 5$ . Note that this decreases the probability on the vertical axis corresponding to  $n = 6$  relative to the one corresponding to  $n = 5$ , thus contributing to create a downward (not upward) sloping hazard function.

that do not experience any price adjustments even at the time when  $n$  price adjustments are already conducted by other retailers tend to be those with relatively low probabilities of price changes. It is well known that such heterogeneity across retailers in terms of the probability of price adjustments creates downward sloping hazard functions (see, for example, Alvarez et al. 2005). Importantly, the same argument continues to hold even if a common shock does not occur simultaneously to each retailer, as long as the timing of a shock to each retailer is randomly determined. In this case, we still have a downward sloping hazard function.

We may have an upward sloping hazard function if the magnitude of a shock to each retailer is determined depending on the value of  $n$ . For example, consider a case in which those retailers with no experience of price adjustments at the time when four adjustments are already conducted by other retailers (i.e.,  $n = 4$ ) are hit by a larger shock than those retailers with no adjustments when  $n = 3$ , and similarly those retailers with no adjustments when  $n = 5$  are hit by an even larger shock, and so on. In this case, we indeed have an upward sloping hazard function, although it seems quite difficult to justify why the magnitude of a shock is related to the value of  $n$  in this particular way.

## 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 in this setting 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 margins, 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  $\alpha$ . Then the target price of this retailer, which is denoted by  $P_{it}^*$ , is given by

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

where  $\omega$  is a parameter between 0 and 1, 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  $\Lambda$  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,  $x$ , this indicates state-dependent pricing, and if not, this indicates 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:

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

where  $\lambda_0$  is a positive parameter. The value of  $\lambda_0$  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  $\alpha$  is based on the empirical autocorrelation in the frequency of changes in the lowest price.<sup>16</sup>

## 4.2 Simulation results

The simulation results are presented in Figure 9. The left panel shows autocorrelations for the size and the frequency of price changes. The result clearly shows that there is a positive autocorrelation both in the intensive and the extensive margin, although the autocorrelation is slightly larger and longer for the extensive margin than for the intensive margin. Note that such persistence in the intensive and the extensive margin stems from strategic interactions among retailers due to the presence of strategic complementarities described by equation (1). Comparing this result with the empirical result presented in Figure 7, we see that the

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<sup>16</sup>To test the robustness of our results, we also conducted simulations with slightly smaller values of  $\alpha$  ( $\alpha = 0.8$  and  $0.7$ ), as well as different values of  $\omega$ . The results are similar to the one reported in the text.

persistence in the extensive margin is consistent with what we saw in the data, but there is an important difference for the intensive margin 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 (i.e.,  $\Lambda(x)$  is decreasing for  $x < 0$  and increasing for  $x > 0$ ), higher (lower) probability of price adjustments tends to be associated with greater (smaller) size of adjustments. This feature is clearly 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.

Turning to the right panel of Figure 9, this shows the probability of a price adjustment by retailer  $i$  conditional on the occurrence of the  $n$  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 adjustments, 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. Our main finding is that there is a positive autocorrelation in the frequency of price adjustments, implying that there tends to be a 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 experiences, on average, five rounds of price adjustments before the entire process of adjustments is completed. Also, we have found an upward sloping hazard function in the sense that the

probability of price adjustments for a given retailer increases with the number of previous adjustments conducted by his rivals since his last price adjustment. We interpret these findings as evidence for the presence of strategic complementarities in price setting.

Can we carry over these results to the world outside internet markets? Probably no, because pricing behavior in online markets may be quite different from the one in offline markets. Does there exist a similar clustering in price adjustments outside internet markets? If so, is it large enough to account for the difference between price stickiness at the micro and macro levels? These are the questions to be addressed in future work.

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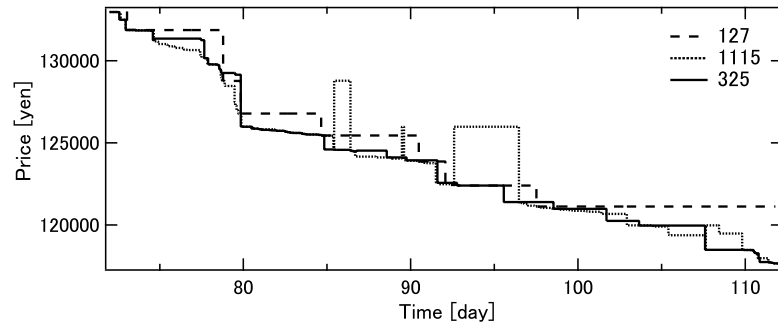
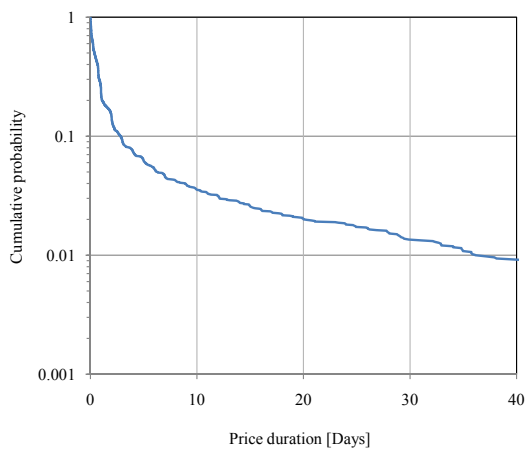
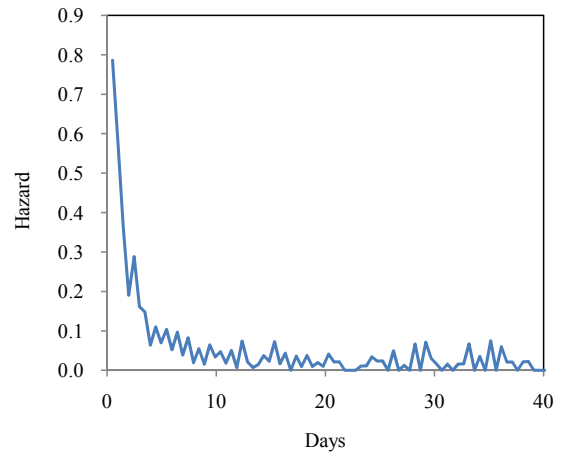


Figure 1: Illustration of prices offered by competing retailers



(a) Cumulative distribution function



(b) Hazard function

Figure 2: Price duration of an LCD TV

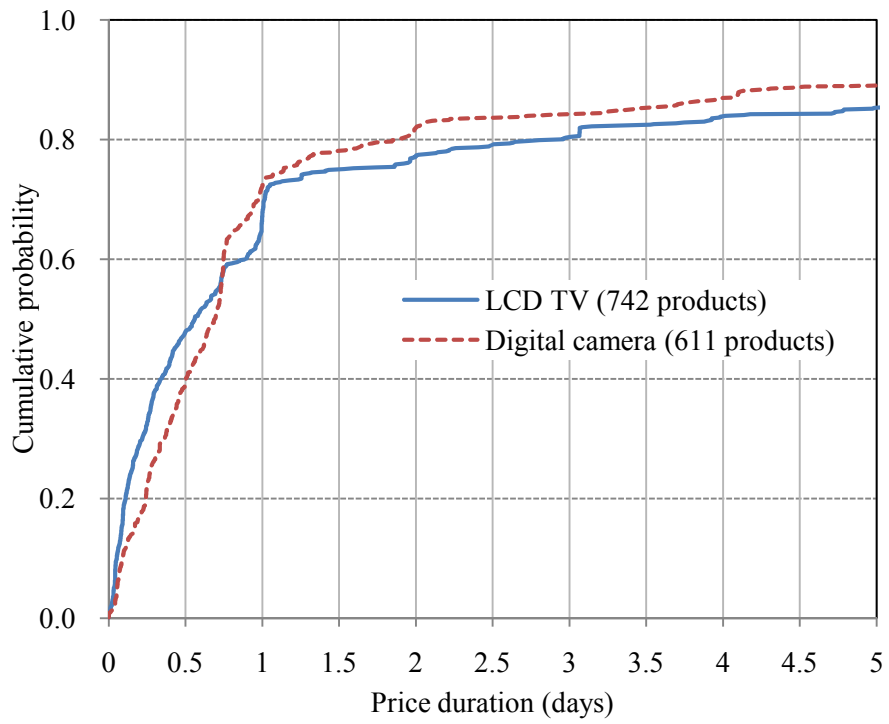


Figure 3: Price duration by product

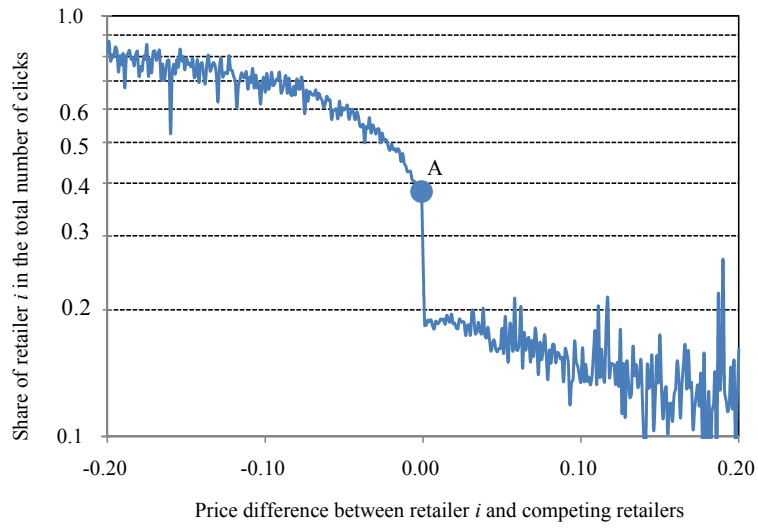


Figure 4: Relative price and the share in the number of clicks

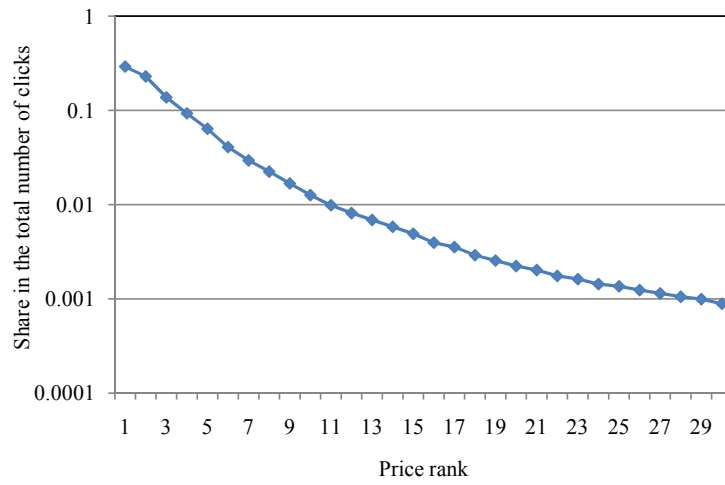


Figure 5: Price rank and the share in the number of clicks

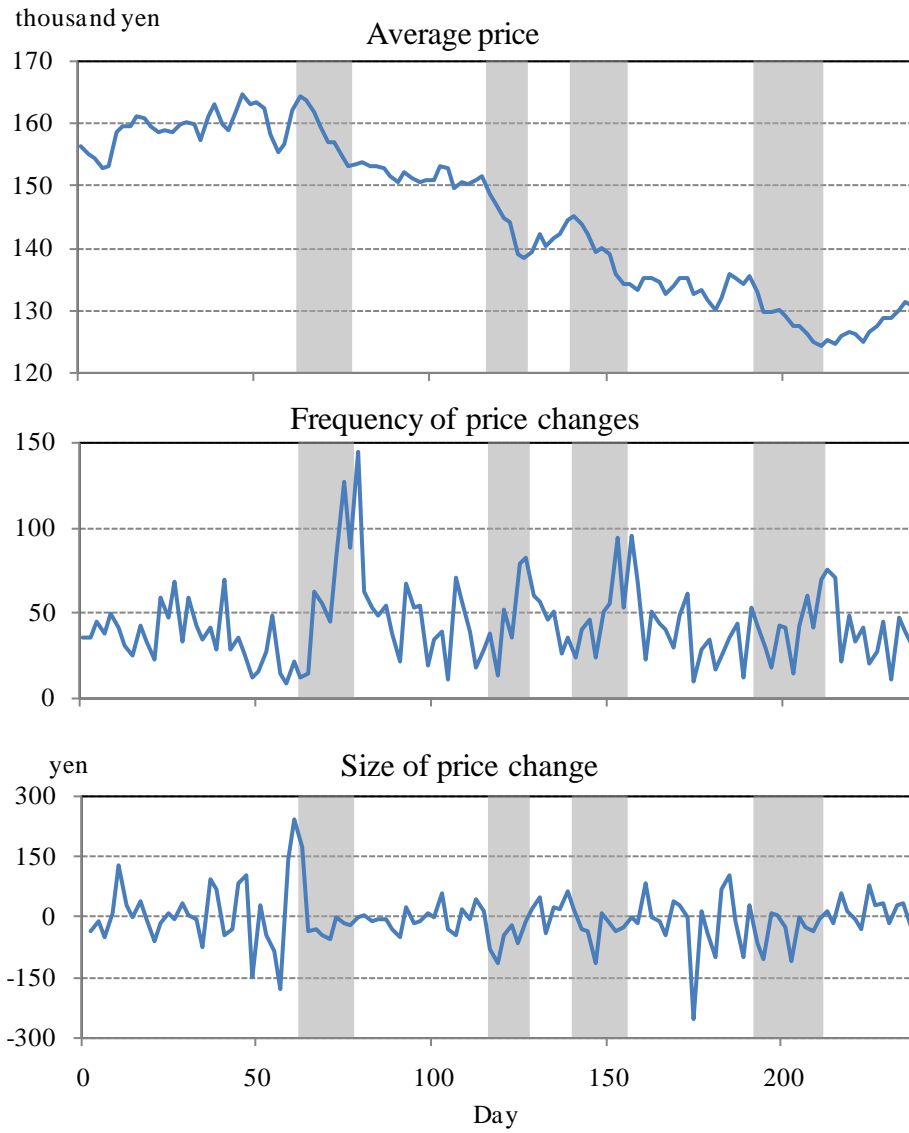


Figure 6: Fluctuations in the average price of an LCD TV

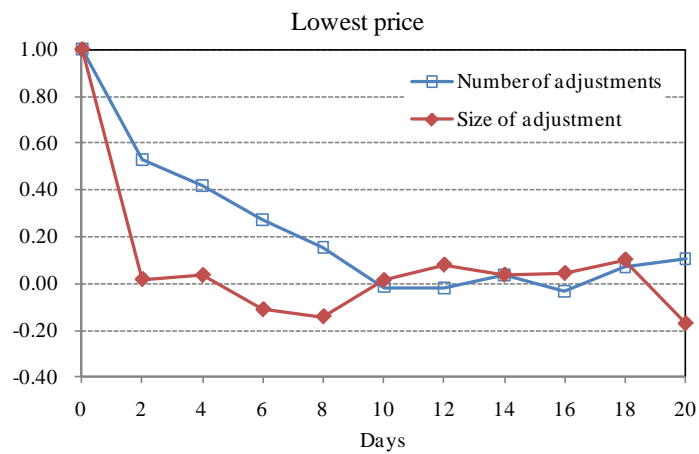
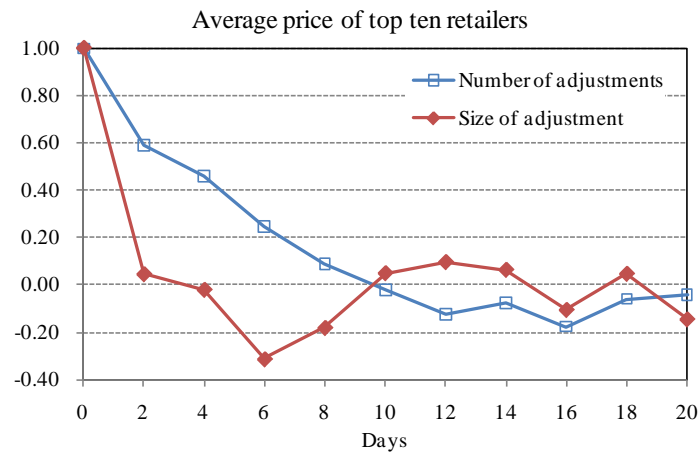
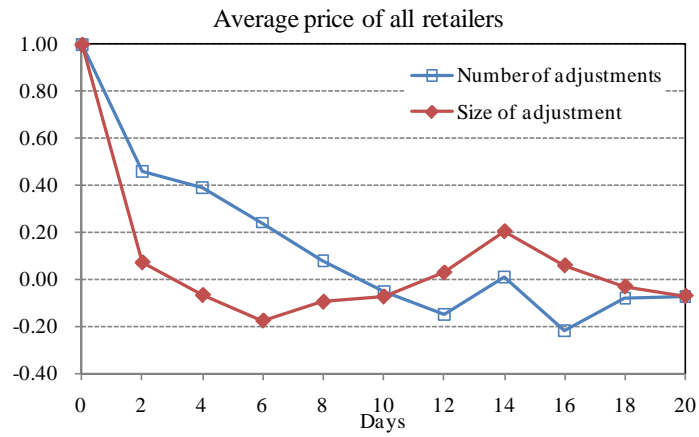


Figure 7: Autocorrelation functions of the intensive and extensive margins

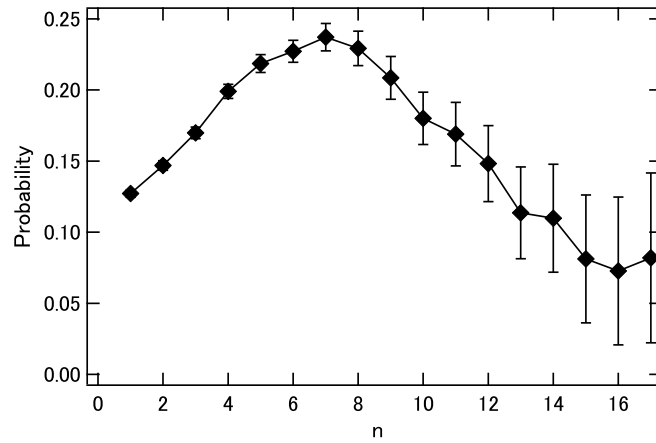
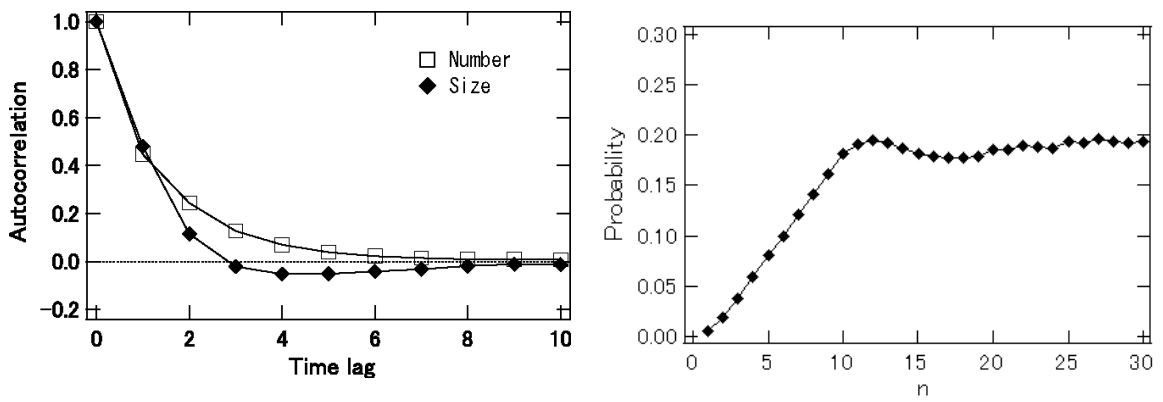


Figure 8: Probability of price adjustment conditional on the number of adjustments by rivals



(a) Autocorrelations in the intensive and extensive margins (b) Probability of price change conditional on the number of changes by rivals

Figure 9: Simulation results