Price levels, Price Dynamics, and Low-Price Guarantees*

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Abstract

In this paper, we investigate how low-price guarantees (LPGs) affect store price levels and price dynamics. In particular, we focus on three dimensions of LPGs, refund depth, length of search period and whether allowing own price-matching (OPM). We use a unique data set consisting of 33,587 daily price quotes collected from five major online consumer electronics retailers, each with a different LPG. We find that (i) price-beating LPGs lead to higher prices and more frequent yet larger price adjustments than price-matching LPGs; (ii) stores offering OPM charge higher prices and adjust prices more frequently but with smaller magnitudes than those do not offering OPM. Thus, we conclude that less restrictive LPGs facilitate higher prices, which is supportive of the conventional view that price-matching policies can discourage price undercutting.

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1 Introduction

Best Buy (*store A*) has the following statement at its web site:

"Our price-matching policy applies to **the current week's prices compared to the previous week's prices**, and to how our prices compare with our competitors'... If, within 30 days (...) of your purchase from Best Buy, you find a local competitor (...) offering a lower price on an available product of the same brand and model, we'll refund the difference plus another 10% of the difference."

Its rival, Circuit City (*store B*) has the following statement at its web site:

"If you've seen a lower advertised price from a local store with the same item in stock, ...we'll gladly beat their price by 10% of the difference. Even after your purchase, if you see a lower advertised price (**including our own sale prices**) within 30 days, we'll refund 110% of the difference. Our Price Match Plus Guarantee means you don't have to wait for a sale to know you're getting the best price."

– Both were quoted on July 16, 2003.

Recent advances in information technology have dramatically changed the manner in which consumers gather information about products and prices. With the aid of such tools as price-comparison sites (e.g., pricegrabber.com and pricewatch.com), consumers nowadays can easily locate the best available deals online. Many stores, especially those selling consumer electronics, office supplies, furniture and alike, often guarantee to match any lower prices to attract savvy shoppers. Notice that low-price guarantees (LPGs) may differ in several dimensions.[1] Some LPGs sound more appealing than others, such as offering larger

[1] *Refund depth* is defined as the amount of reimbursement promised by the store, *own price-matching* as whether a store offers to include its own prices in its LPG, and *length of search period* as the number of days allowed for post-sale search.

refunds, own price-matching, or longer post-sale search periods, *ceteris paribus*. For instance, when stores promise to beat others' prices, consumers pay even less than the best advertised prices.[2]

In the literature, whether LPGs are anti-competitive has been a well-debated topic. On the one hand, the collusion theory suggests that LPGs encourage collusion and are anti-competitive; on the other hand, the price-discrimination theory argues that LPGs enhance competition and are pro-competitive. Yet, empirical studies on this topic are few.[3] The present paper contributes to the literature by examining a unique data set on consumer electronics. In addition, the existing literature has been taking a static view by focusing on how different LPGs affect the level of prices but not price dynamics (i.e., the frequency and the magnitude of price adjustments). To the best of our knowledge, the present paper is a first attempt to fill in this gap.

In this paper, we address the following issues: (i) the effects of LPGs on the level of prices; and (ii) the effects of LPGs on the frequency and the magnitude of price adjustments. We collect a unique data set of 33,587 daily price quotes for 109 popular products sold at five major consumer electronics retailers (Best Buy, Buy.com, Circuit City, Compusa and Sears) between July 2003 and April 2004. Each of the five stores carries a different LPG (see the summary in Table 1).[4] First, Best Buy and Circuit City offer to own-price matching (OPM) while the other three do not. Second, Circuit City, Best Buy and Sears promise to beat any lower prices, while Buy.com and Compusa only promise to match. Third, Best Buy, Circuit City and Sears allow 30 days of post-sale search, and the other two allow shorter search periods. Taken together, this sample allows us to compare the competitiveness across different LPGs. Our analysis is comparable to those comparing stores with and without LPGs in the existing literature.[5]

We find that PB are associated with higher prices than PM by 1.6%, which is supportive of Sargent's (1993) argument that PB is more effective in discouraging price-cutting than PM. Our findings, however, differ from those in Arbatskaya et al. (2006) who find that PMs

[2]For example, consider the two stores A and B in the earlier quotes. Suppose that $p_A > p_B$. One who purchases from store A can request a price-beating. She then pays only $p_A - 110\% \times (p_A - p_B) = p_B - 10\% \times (p_A - p_B)$. The second term of the above equation is her savings from requesting a price-match. Effectively, she pays less than the lowest advertised price p_B.

[3]To date, only a handful have tested the theories, including Arbatskaya et al. (1999; 2006), Hess and Gerstner (1991) and Manez (2006).

[4]Store reputation is a very important factor affecting consumers' purchasing decisions online. With only five stores, we minimize the reputation heterogeneity across stores.

[5]For example, we test whether or not allowing price-beating (PB) more effectively discourages rivals from undercutting than allowing price-matching (PM), and similarly, whether or not allowing OPM is more effective than without OPM.

facilitate higher prices but PBs do not, and also from those in Moorthy and Winter, who find that the lowest-price firms are more likely to adopt LPGs.[6] Such departure may be due to the difference between our product selections and theirs. In addition, the regression results also suggest that allowing OPM raises average prices by 1% and a longer post-sale search period by up to 0.9%, both at the 1% significance level. In short, we conclude that less restrictive LPGs facilitate higher prices.

We find that prices are more likely to decline than to rise, with the exception for Buy.com. Substantially reduced menu costs for online-only stores (e.g., Buy.com) may explain this observation. In addition, we find the average magnitude of price decreases is greater than that of price increases. Furthermore, stores offering different LPGs vary greatly regarding the frequency and the magnitude of price adjustments. Holding other factors constant, stores offering OPM has larger price increases but smaller decreases than those absent from such an offering. Compared to those with PM, stores with PB has both larger price increases and decreases. Regarding the frequency of price adjustments, although stores offering PB are more likely to run sales, their average prices are still higher than those offering PM. Finally, whether allowing OPM or the length of post-sale search do not systematically affects the direction of price adjustments.

The rest of the paper is organized as follows. Section 2 reviews the related literature. In section 3, we discuss the data and provide summary statistics. Section 4 contains the analysis and results, and we conclude in section 5.

2 Overview of Related Literature

Earlier studies on price-matching mainly focus on the incentive theory.[7] One strand of the literature is concerned with the potential anti-competitiveness of LPGs. Although LPGs appear to facilitate competition, they often discourage price-undercutting (see Salop, 1986; Doyle, 1988; Edlin, 1997; Dixit and Nalebuff, 1991). However, Corts (1995) and Hviid and Shaffer (1999) express an alternative view. Corts (1995) shows that the anti-competitive argument is contingent with the fact that firms adopt PM. For example, if firms adopt PB,

[6] The difference may stem partly from the fact that Moorthy and Winter include small players in their sample, while all five stores in ours are large national chains and usually charge higher prices than smaller ones in the same market.

[7] A relevant literature is the one on most-favored-nation or most-favored-customer clauses (e.g., Cooper, 1986; Crocker and Lyon, 1994), since announcing a price-matching policy is equivalent to implicitly sign a most-favored-customer contract with customers who are aware of this policy.

the competitive outcome resumes.[8] Hviid and Shaffer introduce hassle costs and argue that if consumers must request refunds (therefore incurring hassle costs), any increase in equilibrium prices due to price-matching will be small (if any), even if hassle costs are arbitrarily small. Higher prices sustain, however, in asymmetric markets, although prices fall well below the maximal joint profits.

Another strand of the earlier literature focuses on the price discriminate theory. Corts (1997) points out that studies often treat coupons as a means of price discrimination while treat LPGs primarily as a facilitation device for high prices, despite the similarities between the two. In a price-discrimination model, he shows that firms with LPGs may charge either higher or lower equilibrium prices than those without. Chen et al. (2001) consider heterogeneous consumer groups with different search costs and store loyalty (namely, "switchers", "loyals", "bargain shoppers" and "opportunistic loyals"). They argue that because of the existence of "opportunistic loyals", adopting LPGs generates both "competition-dampening" and "competition-enhancing" effects. Similar to Corts (1997), they also suggest that LPGs can be either anti- or pro-competitive. Png and Hirshleifer (1987) allow firms to discriminate between informed and uninformed consumers. They find that listing prices increase and total sales decrease in the number of firms. When firms coordinate, discrimination becomes more efficacious, which leads to even higher profits.

Recent studies often focus on the information component of LPGs. Through experiments, Srivastava (1999) concludes that consumers perceive LPGs of facilitating low, not high prices. Moorthy and Winter (2006) incorporate the signaling theory into their analysis in which obtaining price information is costly. They argue that low-price firms use LPGs to communicate effectively with uninformed consumers, and provide supportive empirical evidence of the signaling theory against the alternatives – the collusion and price discrimination theories.

Despite an extensive theoretical literature on LPGs, empirical studies are limited. Hess and Gerstner (1991) document a LPG policy change by a supermarket. Their analysis indicates that LPGs with PM facilitate high prices, supporting the collusion theory. A related study, Manez (2006) observes the adoption of a PB policy and finds supportive evidence of the signaling theory. Arbatskaya et al. (1999) study auto tire prices advertised in Sunday newspapers and find that the advertised tire price increases in the number of firms offering LPGs in the same market. Arbatskaya et al. (2006) use the same data set but distinguish (1) PM from PB and (2) selling from advertised prices in different LPGs. They argue that

[8] However, Edlin (1997) and Kaplan (2000) find that when LPGs are applied to selling rather than advertised prices (Corts (1995) assumes the latter), the supracompetitive outcome reappears. Our empirical results suggest that PB is associated with higher prices than PM.

firms use PM to facilitate higher prices but use PB for a different purpose. Furthermore, they find LPGs applying to selling prices are more likely to discourage undercutting than advertised prices. Apart from the existing studies, our contribution is to incorporate the dynamic component of pricing strategies in different LPGs.

3 Data

3.1 Data Collection

We wrote programs to download information from five online stores (Best Buy, Buy.com, Circuit City, Compusa and Sears) daily at a certain time. The entire process usually took approximately 5 minutes. All relevant information (such as prices, rebates etc.) were then extracted from the saved web pages. In total, we have collected about $50,000$ daily price listings for popular consumer electronics products sold at these five online stores between April 1, 2003 and March 31, 2004.

Since Circuit City was the only store that offered OPM at the beginning of our data collection, our product selection was based on whether Circuit City and at least one other store carried the same item. That is, we removed the product once Circuit City discontinued to sell, or once Circuit City was the only one selling it. Either occurred frequently due to the launch of new models. In the final sample, we have a total of 33,587 daily price quotes for 109 consumer electronics products.[9]

Finally, note that all price quotes in the sample are pre-rebate and pre-discount. Casual observations reveal that stores sometimes offer promotions such as mail-in rebates and instant store discounts. For instance, occasionally, at Best Buy and Circuit City, one has to place a product in the online cart to obtain a final price quote, which entails an instant store discount. Unfortunately, our electronic agent was unable to perform such a task. Since we have the information indicating whether a promotion was offered, we construct two dummy variables, *Instant Store Discount* and *Mail-in Rebate* to measure the qualitative effects of these offers.[10]

[9] We dropped the observations with abnormally high or low prices. For example, a "SOLD OUT" product had a very low price. We consider a price quote as "normal" if it is between twice and half of the same-store average for the same item.

[10] Eliminating these observations from our analysis does not change our main findings.

3.2 Descriptive Statistics

Table 2 reports the distribution of the number of stores carrying the same products during the sample period. Our product selection criteria determines that the majority of the products (or about 99%) are offered by at least two stores, while all five stores sell about 30% of the products at the same time. In the sample, stores often carry different brands and/or models of the same product as a way to soften the competition.[11]

Table 3 provides summary statistics of prices by policy dimensions. There are noticeable disparities across different categories within each policy dimension. Compared to PM, PB is associated with much higher average prices ($502.45 vs. $398.49); allowing OPM is associated with lower prices than otherwise ($462.15 vs. $475.92); allowing a longer search period leads to higher average prices. These observations are subject to a number of factors (e.g., different product mixes), for which we will control later in the regression analysis.

Table 4 compares average prices by store-pair. Five stores translate into ten store-pairs. The only difference between each matched pair of observations is where the price quotes are obtained. There are a total of 26,581 such pairs. For each pair of stores, we report three numbers in Table 4. The first number is the average difference between the two stores. A negative sign implies that the store on the left charges a higher average price than the one on the top line.[12] The second number is the standard deviation and the third is the number of paired observations. Among the five stores, Best Buy always has a higher average price when at least one other store also carries the same product, while Buy.com has the lowest average prices.

4 Analysis and Results

In this section, we analyze price levels and price dynamics in the sample. We first discuss the effects of LPGs on price levels, and then compare general price dynamics across stores and establish connections between them and different LPGs.

[11] This is especially the case for Best Buy and Circuit City. These two close competitors tend to differentiate from each other, making it difficult to find identical products at both stores at the same time.

[12] With two stores, say, A and B with prices p_A and p_B, there are two measures for price difference: absolute ($p_B - p_A$) and relative ($\frac{p_B - p_A}{p_A}$). Table 4 presents the absolute difference in prices. If, instead, we use the relative measure, the results are qualitatively the same. Specifically, the signs are the same except for the case of Best Buy vs. Circuit City. It becomes significantly positive (0.56%) when we use the relative measure.

4.1 Price Levels and LPGs

In the section, we examine the effects of LPGs on the price level. Our primary objective is to test whether there are systematic difference in prices across different LPGs, measured by different dimensions.

$$\begin{aligned} \ln(P_{ijt}) &= \alpha_0 + \alpha_1 * PB + \alpha_2 * OPM + \alpha_3 * 30Day + \alpha_4 * 14Day + \\ & \alpha_5 * \textit{Instant Store Discount}_{ijt} + \alpha_6 * \textit{Mail-in Rebate}_{ijt} + \alpha_7 * CPI_t + \beta * \mathbb{X}_j + \varepsilon_{ijt} \end{aligned} \quad (1)$$

The left-hand-side of the above equation is the natural logarithm of a price quote for product i sold at store j at week t. We consider three dimensions of LPGs.

- Price-Beating dummies: PB equals one if store j promises to refund 110% of the price difference, and zero if the store only promises to match the difference. A positive coefficient suggests that average prices is higher for PB than for PM.
- OPM dummies: OPM is defined as one if store j allows OPM and zero otherwise. A positive coefficient suggests that allowing OPM results in higher average prices.
- Search Length dummies: Depending on length of search, $30Day$ ($14Day$) is defined as one if store j allows 30 (14) days for post-sale search. Dummy $3Day$ is omitted in the regressions. A positive coefficient suggests that average prices increase in the length of search period.

We also define two store promotion dummies. $\textit{Instant Store Discount}_{ijt}$ ($\textit{Mail-in Rebate}_{ijt}$) is defined as one if store j offers an instant store discount (a mail-in rebate) for product i at week t and zero otherwise. CPI refers to the monthly consumer price index published by the Bureau of Labor Statistics.

Following Baye et al. (2006), we define vector $\mathbb{X}_{ijt}$ to control for: (1) number of competing stores; (2) product fixed effects; (3) month fixed effects; and (4) product life-cycle fixed effects, which are the interactions between product and month dummies. Finally, ε_{ijt} is the error term in the regression.

Table 5 reports the estimated results, which suggest that different dimensions of LPGs affect prices. A store using PB in its LPG charges higher average prices than one using PM by 1.6%. This finding is supportive of Sargent's (1993) argument that PB is more effective to discourage undercutting than PM. It is, however, in contrast to the findings in Arbatskaya et al. (2006) which conclude that PB is likely to be associated with lower prices than PM and to that in Corts (1995) which finds that PB leads to competitive prices.

Next, allowing OPM raises average prices by 1%. Allowing 30 (14) days of post-sale search increases average prices by 0.9% (0.3%), suggesting that hassle costs increase exponentially in the length of search period.

The model specification also includes two store promotion variables, *Instant Store Discount* and *Mail-in Rebate*, both of which measure qualitatively the effects of such promotion activities. Everything else equal, our analysis indicates that having a mail-in rebate raises average prices by 4.9%, while having an instant store discount lowers average prices by 0.3%.

In summary, in Table 5, we compare LPGs with different degrees of restrictions. In particular, we treat LPGs with PB, OPM, or a longer post-sale search period as less restrictive than those with PM, no OPM, or a shorter search period, respectively. In the literature, studies claim that LPGs can either raise or lower equilibrium prices (e.g., Corts, 1997; Chen et al., 1999). Under the above definitions, our findings shed some light on the view that less restrictive LPGs facilitate higher prices.[13]

4.2 General Price Dynamics

Next, we analyze the patterns of price adjustments in the sample. Tables 6a,b & 7a,b report price adjustments by stores. In Table 6a, 74 out of 109 products (or 68%) incur price adjustments during the sample period. Among others, Buy.com and Sears have the highest percentage (70%) of products changing prices. As expected, the pure online retailer, Buy.com adjusts its prices most frequently, or 533 counts during the sample period. Compared to multi-channel retailers, it has relatively lower menu costs. For instance, price changes at Best Buy during the same period only count 32 in total.

Depending on stores, even the same product may exist in the sample for different lengths of time. Thus, we normalize the number of price adjustments into a fixed 60-day period.[14] The last three columns in Table 6a reports the normalized number of changes by stores, which take into consideration the heterogeneities in products across stores. Again, Buy.com takes the lead with 203.3 counts of price changes, followed by Circuit City, and Best Buy tends to have very sticky prices.

Hosken and Reiffer (2004) examine retail price variations for a variety of goods and

[13] Using retail data collected at PriceSCAN.com, Moorthy and Winter find that stores with LPGs usually offer lower prices than those without. A drawback of their sample is the large amount of store heterogeneity. For instance, online branches of major multi-channel retailers such as Circuity City and Sears are listed side by side with less-known stores such as PricesRite (a Yahoo! store), BH Photo and electronics.com.

[14] For example, say a product carried by Circuit City has 6 price changes in a 180-day period. Then the unnormalized number of price changes for this product by Circuit City is 6, and the normalized number (which we call Frequency later in the paper) is $6 \times \frac{60}{180} = 2$.

regions in the U.S. They find that groceries' prices are typically quite sticky, and change only up to half of the time. Prices always return to the same level following occasional sales. This implies that the frequency and the magnitude of price increases and decreases almost offset each other. Moreover, the number of products with price increases is close to that of products with price decreases. However, this is not the case for the products in our sample.[15] In Table 6a, prices are more likely to decline than to rise, due to the nature of consumer electronics products.

Table 6b summarizes the number of price adjustments by LPG type. First, compared to those adopting PB, stores adopting PM carry fewer products with price changes. Yet, stores offering PM adjust prices more frequently (640 counts) than those offering PB (195 counts). Second, allowing OPM reduces a store's incentive to frequently adjust prices and thus leads to relative sticky prices, 147 vs. 688 counts. Third, it is expected that stores adjust prices more frequently if they allow a short post-sale search period.

Furthermore, Table 6b also compares the numbers of price increases and decreases by LPG type. Interestingly, asymmetry between increases and decreases in price rises in some LPGs but not others. Specifically, prices are almost equally likely to increase and to decrease for PM or non-OPM while prices are far more likely to decrease than to increase for PB or OPM. As for post-sale search periods, asymmetry in price adjustments only appears when allowing 30-day search.

Tables 7 report price adjustments during two consecutive days by store.[16] Generally speaking, prices are relatively sticky on the daily base, and prices are more likely to decline than to rise following a "no change". In addition, conditional on a price decrease (increase) on the previous day, prices are more likely to rise (drop) than to drop (rise) the following day.

Tables 8a&8b summarize the magnitude of price adjustments. In both tables, *Depth* refers to the average of price increases (decreases) as a fraction of average prices.[17] Table 8a reports the results by store and Table 8b reports by LPG type. In general, the asymmetry in the magnitude between decrease and increase is more apparent in Table 8a than in Table 8b. In Table 8a, except for Circuit City, other stores has a larger magnitude in an average price decrease than an average increase. For instance, at Best Buy, the average depth of price increase is 8.4%, compared to 12.6% of price decrease. In Table 8b, PB (OPM) is

[15] We have a product selection problem, partly due to our data collection criterion (i.e., popular electronic products carried by Circuit City and at least one other store), and partly due to possible strategic selections by stores. That is, different stores may choose to compete on different sets of products.

[16] We also separate "no posting" from "no change", and find the similar pattern.

[17] We expect some products to be double counted in columns 2 and 4 since the same product may incur both price increases and decreases during the sample period.

associated with a larger magnitude of price adjustments than PM (non-OPM). While no systematic correlation arises between the post-sale search length and the magnitude of price adjustments, allowing 14-day search is associated with the largest levels of price changes.

However, the findings in this section are subject to a downward bias due to the way that we compute the non-normalized and normalized price changes (increase, decrease and frequencies). Note that our sample is truncated both from the starting and the ending dates, and there might be missing observations in between. Should those missing data involve any price changes, our findings would be underestimated.[18] Finally, the use of mail-in rebates and instant store discounts also affects the frequency and the magnitude of effective price adjustments.

4.3 Price Dynamics and LPGs

The previous section documents the asymmetry in price dynamics across stores as well as LPG types. Next, we explore the correlation between price adjustments (i.e., the frequency and the magnitude) and different LPGs. Thus, we estimate in turn the following two equations

$$Depth_{ijt} = \alpha_0 + \alpha_1 * PB + \alpha_2 * OPM + \alpha_3 * 30Day + \alpha_4 * 14Day + \varepsilon_{ijt},$$

and

$$Indicator_{ijt} = \alpha_0 + \alpha_1 * PB + \alpha_2 * OPM + \alpha_3 * 30Day + \alpha_4 * 14Day + \varepsilon_{ijt}.$$

In both equations, each observation unit is a product-store. $Depth_{ijt}$ is defined as a price increase (decrease) as a fraction of the same store average, and measures the magnitude of product i's price adjustments in store j at time t. price $Indicator_{ijt}$ indicates whether store j increases or decreases the price for product i at time t.[19]

We use the magnitudes of price increase and decrease as the dependent variables, respectively and report the estimated results in columns (1)&(2) in Table 9. Holding other factors constant, stores offering OPM has larger price increases but smaller decreases than those absent from such an offering, or by 0.029 and -0.01, respectively. Compared to PM, PB has both larger price increases and decreases. Finally, having 14-day of post-sale search is

[18] For instance, our automated data collection was occasionally interrupted due to changes in web design at some stores.

[19] The results in Tables 7a&7b suggest that prices are very sticky in the market of our interest. Here we only consider whether prices are more likely to rise or fall, ignoring the dominant case of "no price change".

associated with greater price fluctuations in both directions than either having 30- or 3-day.

Column (3) reports the results of a probit regression model. Stores offering PB are more likely to run sales than those with PM. Note that in Table 5, we find that product prices are 1.6% higher for stores with PB. Taken together, these findings suggest that although PB has more sales, its average prices are still higher than PM. In addition, whether allowing OPM or the length of post-sale search do not systematically affects the direction of price adjustments.

5 Conclusions

It is often difficult to construct counterfactual situations where LPGs are absent. As an alternative, this paper compares different types of LPGs. First, we study the extent to which different dimensions of LPGs facilitate the competition. Our analysis concludes that (1) stores offering PB charge higher average prices than those offering PM; (2) stores offering OPM also charge higher prices than those do not; and (3) a longer post-sale search period leads to higher prices. To some extent, our findings shed some light on the traditional view that less restrictive LPGs actually facilitate high prices.

In this paper, we also study the extent to which different LPGs systematically affect price adjustment patterns. We find that prices are more likely to decline rather than to rise, and the average magnitude of price decreases is greater than that of price increases. Furthermore, stores offering different LPGs vary greatly regarding the frequency and the magnitude of price adjustments. Holding other factors constant, stores offering OPM has larger price increases but smaller decreases than those absent from such an offering. Compared to those with PM, stores with PB has both larger price increases and decreases. Regarding the frequency of price adjustments, although stores offering PB are more likely to run sales, their average prices are still higher than those offering PM. Finally, whether allowing OPM or the length of post-sale search do not systematically affects the direction of price adjustments.

However, one need to take caution when interpreting these results. For one thing, our online price quotes exclude possible shipping charges. However, shipping is an important factor when consumers shop online. Furthermore, we might omit other factors that possibly affect how stores run promotions. These include, but certainly not limited to, the extent to which hassle costs are when submitting price-matching requests at each store, whether a product is available exclusively online or whether a product is at the beginning or the final stage of its life-cycle. We leave these issues for future studies.

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Table 1. LPGs by Store

Store	Refund Depth	Own Price-Matching	Days of Search
Best Buy	PB	Yes	30*
Buy	PM	No	3
Circuit City	PB	Yes	30
CompUSA	PM	No	14
Sears	PB	No	30

*: 14 days for computers, monitors, printers and notebooks, camcorders, digital cameras and radar detectors at BestBuy.

Table 2. Distribution of the Number of Stores Carrying the Same Products During the Sample Period

Number of Stores	Number of Products	Percent (%)
1	1	0.92
2	9	8.26
3	37	33.94
4	32	29.36
5	30	27.52
Total	109	100%

Table 3. Summary Statistics by LPG dimensions

	PM	PB
N	11014	22573
mean	398.49	502.45

stats	OPM	Non-OPM
N	18453	15134
mean	462.1537	475.9202

	30-Day of Search	14-Day of Search	3-Day of Search
N	18619	7324	7126
mean	527.4621	459.4508	413.4424

Table 4. Store-Pair Price Comparison

	Buy.com	Circuit City	CompUSA	Sears
Best Buy	52.805	1.113	10.626	1.385
	(2.384)**	(0.458)*	(0.849)**	(0.632)*
	2499	6136	2168	1800
Buy.com		-29.853	2.902	-12.841
		(1.091)**	(1.483)	(1.901)**
		4226	2138	1085
Circuit City			16.108	3.31
			(0.835)**	(0.295)**
			2658	3225
CompUSA				-22.675
				(1.411)**
				646

Note: The first number is the average difference between each store-pair; the second number is the s.d.; the third
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. Regression Results of the relationship between Price and LPG

Dependent Var: Ln(Price)	(1)
Price-Beating	0.016
	(0.003)***
Own Price-Matching	0.01
	(0.001)***
30-Day of Search	0.009
	(0.001)***
14-Day of Search	0.003
	(0.001)**
Instant In-Store Discount	-0.003
	(0.001)**
Mail-in Rebate	0.049
	(0.002)***
Consumer Price Index	-0.012
	(0.001)***
Number of Firms	Yes
Product Fixed Effects	Yes
Month Fixed Effects	Yes
Product Life-Cycle Fixed Effects	Yes
Constant	6.194
	(0.099)***
Observations	33587
Adjusted R-squared	0.9976

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6a. Price Adjustments by Store: Frequency

Store		Products with	% with	Unnormalized changes			Normalized changes		
	Total	changes	changes	Total	with increases	with decreases	Total	with increases	with decreases
Best Buy	47	20	43%	32	4	28	14.3	2.8	11.5
Buy.com	53	37	70%	533	266	267	203.3	99.3	104
Circuit City	84	43	51%	115	31	84	121.9	34	87.9
CompUSA	38	17	45%	107	51	56	58.6	27.5	31.1
Sears	30	21	70%	48	12	36	19.1	3.4	15.7
Total	109	74	68%	835	364	471	417.2	167	250.2

Table 6b. Price Adjustments by LPG Dimensions: Frequency

Store		Products with	% with	Unnormalized changes			Normalized changes		
	Total	changes	changes	Total	with increases	with decreases	Total	with increases	with decreases
PM	69	45	65%	640	317	323	170.2	81	89.2
PB	92	54	59%	195	47	148	113.8	31.3	82.5
OPM	88	50	57%	147	35	112	114.5	32.4	82.1
Non-OPM	87	58	67%	688	329	359	176.6	80.4	96.2
30-Day	89	48	54%	163	43	120	117.5	31.4	86.1
14-Day	44	27	61%	124	52	72	47.9	20.2	27.7
3-Day	53	37	70%	533	266	267	203.3	99.3	104

? Why for search length, unnormalized changes do not add up to 835?

Table 7. Price Adjustments on Two Consecutive Days - By Store

Best Buy		Day n		
		increase	decrease	no change
	increase	0	0	4
Day n-1	decrease	0	0	28
	no change	4	28	72

Buy.com		Day n		
		increase	decrease	no change
	increase	69	73	124
Day n-1	decrease	76	57	133
	no change	116	136	6238

Circuit City		Day n		
		increase	decrease	no change
	increase	0	3	26
Day n-1	decrease	5	4	71
	no change	26	74	10687

Compusa		Day n		
		increase	decrease	no change
	increase	0	4	47
Day n-1	decrease	21	1	33
	no change	30	51	3626

Sears		Day n		
		increase	decrease	no change
	increase	0	0	12
Day n-1	decrease	1	0	35
	no change	11	36	3965

Table 8a. Price Adjustments by Store: Magnitude

Store	Price Increase		Price Decrease	
	Product	Depth (%)	Product	Depth (%)
Best Buy	4	8.4	18	12.6
Buy.com	30	4.1	35	5
Circuit City	17	9.2	42	7.5
Compusa	18	12.1	20	12.24
Sears	3	5.9	17	8.4

Table 8b. Price Adjustments by LPG Dimensions: Magnitude

Store	Price Increase		Price Decrease	
	Product	Depth (%)	Product	Depth (%)
PM	39	5.41	44	6.23
PB	21	8.28	51	8.68
OPM	19	9.08	47	8.76
Non-OPM	41	5.43	57	6.45
30-Day	20	8.23	50	8.52
14-Day	19	12.04	26	12.67
3-Day	30	4.12	35	4.96

Table 9. Regression Results of Price Adjustments

	(1)	(2)	(3)
Dependent Var	Increase	Decrease	Indicator
Price-Beating	0.019	0.065	-0.843
	(0.022)	(0.019)***	(0.440)*
Own Price-Matching	0.029	-0.01	-0.009
	(0.014)**	(0.011)	(0.231)
30-Day of Search	-0.001	-0.031	0.158
	(0.021)	(0.016)*	(0.388)
14-Day of Search	0.078	0.071	-0.134
	(0.010)***	(0.010)***	(0.123)
Constant	0.042	0.05	0.011
	(0.005)***	(0.006)***	(0.054)
Observations	364	471	835
Adjusted R-squared[Log Likelihood]	0.1198	0.0887	[-550.626]

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%