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Price Points and Price Rigidity

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Abstract—We study the link between price points and price rigidity using two data sets: weekly scanner data and Internet data. We find that "9" is the most frequent ending for the penny, dime, dollar, and ten-dollar digits; the most common price changes are those that keep the price endings at "9"; 9-ending prices are less likely to change than non-9-ending prices; and the average size of price change is larger for 9-ending than non-9-ending prices. We conclude that 9-ending contributes to price rigidity from penny to dollar digits and across a wide range of product categories, retail formats, and retailers.

> Nor does anyone know how important . . . [price points] are in practice.
>
> —Alan Blinder et al. (1998)

I. Introduction

WITH the increased popularity of new Keynesian models, understanding the sources of nominal price rigidity has become even more important.[1] One of the recent theories of price rigidity is price point theory, which Blinder et al. (1998) list among the twelve leading theories of price rigidity. According to the authors (p. 26), practitioners' "belief in pricing points is part of the folklore of pricing." Consistent with this observation, they offer evidence from interviews on the importance of price points. In their study of 200 U.S. firms, they found that 88% of retailers assigned substantial importance to price points in their pricing decisions. Kashyap (1995), the first to explore the link between price points and price rigidity, found that catalog prices tended to be stuck at certain ending prices. After concluding that the observation cannot be explained by existing theories, he offered price point theory as a possible explanation.

As Blinder et al. (1998) note in the opening quote to this paper, however, a major difficulty with price point theory is that not much is known about the actual importance of price points or their relationship to price rigidity. Price points will be particularly important for macroeconomics if they can be shown to contribute to price rigidity across a wide range of products and retailers. The literature offers growing evidence on the use of price points, but there remains a lack of direct evidence linking price points and price rigidity. The literature documenting a link between price points and price rigidity using U.S. data is limited to Kashyap (1995) and Blinder et al. (1998). Kashyap has emphasized the need for more direct evidence, stating that a "study focusing on more goods . . . would have much more power to determine the significance of price points" (p. 269).

Our goal is to fill this gap in the literature by offering new evidence on the link between price points and price rigidity using two particularly appropriate but different data sets. One is a large weekly scanner price data set from a major midwestern U.S. retailer, covering 29 product categories over an eight-year period. The second comes from the Internet and includes daily prices over a two-year period for 474 consumer electronic goods, such as music CDs, digital cameras, and notebook PCs, from 293 different e-retailers, with a wide range of prices. Taken together, the two data sets cover a diverse set of products, a wide range of prices, different retail formats, and multiple retailers and time periods.

We found that 9 is the most popular price point for the penny, dime, dollar, and the ten-dollar digits across the two

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[1] See, for example, Carlton (1986), Cecchetti (1986), Warner and Barsky (1995), Danziger (1999, 2007), Dutta, Levy, and Bergen (2002), Levy et al. (2010); Ball and Romer (2003); Rotemberg (1987, 2005, 2010); Nakamura and Steinsson (2008, 2009); Kehoe and Midrigan (2010); Klenow and Kryvtsov (2008); Eichenbaum, Jaimovich, and Rebelo (2011); Alvarez, Lippi, and Paciello (2010); and Midrigan (2011). For recent surveys, see Willis (2003), Wolman (2007), and Klenow and Malin (2011).

data sets. The most common price changes are those that keep the terminal digits at these 9-endings. When we estimated the probability of a price change, we found that the 9-ending prices are less likely to change in comparison to non-9-ending prices. For the supermarket chain in this study, 9-ending prices are 43% to 66% less likely to change than non-9-ending prices. For the Internet data, these probabilities are in the range of 25% to 64%. The average size of the 9-ending price changes is larger in comparison to non-9-ending prices, which further underscores the extent of the 9-ending price rigidity.

The paper is organized as follows. We describe the data in section II. In section III, we study the distribution of price endings. In section IV, we assess the distribution of price changes. In section V, we estimate the effect of 9-endings and 99-endings on price rigidity. In section VI, we evaluate the link between price points and the size of price changes. In section VII, we discuss the robustness of the findings. Section VIII concludes.

II. Two Data Sets

Kashyap's (1995) price point theory suggests that price points should be most important to retail firms (Blinder et al., 1998; Stahl, 2010). We examine retail prices from two large data sets. One is weekly price data for 29 different supermarket product categories over an eight-year period at one supermarket chain. The other contains daily prices from the Internet on products that include music CDs, DVDs, hard disks, and notebook PCs, among others.

The two data sets cover a wide variety of products, a wide range of prices, and different retail formats. In addition, although the supermarket prices are set on a chain-wide basis, our Internet data come from many different retailers, which presumably employ different pricing decision models. Thus, the conclusions that we draw are not specific to a particular retail format, retailer, product, or price range.

Our large supermarket chain, Dominick's, is in the Chicago metropolitan area. During the period of our study, it operated 93 stores with a market share of about 25%. The data consist of up to 400 weekly observations of retail prices in 29 product categories, covering the period from September 14, 1989, to May 8, 1997. The prices are the actual transaction prices as recorded by the chain's checkout scanners. If an item was on sale, the price data reflect the sale price of the item.

Although Dominick's prices are set on a chain-wide basis at the company headquarters, there is some price variation across the stores depending on the price tiers to which the stores belong. Dominick's divides its stores into four price tiers: "Cub fighter," "low," "medium," and "high." The stores designated as Cub fighters are typically located in proximity to a Cub Foods store and thus compete directly with it. The other three price tier stores employ a pricing strategy that fits best given their local market structure and competition conditions.

We report results from analyzing the prices in four randomly chosen stores—one from each price tier: stores 8 (low price tier), 12 (high price tier), 122 (Cub fighter), and 133 (medium price tier). To study the behavior of regular prices, we removed data points if they involved bonus buys, coupon-based sales, or simple price reductions. For this, we relied on Dominick's data identifiers, which indicated such promotions. Dominick's did not use loyalty cards during the period studied.

The Dominick's data contain over 98 million weekly price observations on 18,037 different grocery products in 29 product categories.[2] The four-store sample contains 4,910,129 weekly price observations on 16,105 different products. Barsky et al. (2003), Chevalier, Kashyap, and Rossi (2003), and Levy et al. (2010) offer more details about the data.[3] Table 1 presents descriptive statistics for the Dominick's data for the four stores.

Our Internet data were obtained through the use of a price data-gathering software agent. We programmed it to download price data from BizRate (www.bizrate.com), a popular price comparison site. It accessed the site for data collection from 3:00 A.M. to 5:00 A.M. over a period of more than two years from March 26, 2003, to April 15, 2005. We generated a large sample of product IDs using stratified proportionate random sampling (Wooldridge, 2002) from a list of products available at BizRate. The software agent automatically built a panel of sales prices given the product IDs.[4] The resulting data set consists of 743 daily price observations for 474 personal electronic products in 10 product categories from 293 different Internet-based retailers. The categories were music CDs, movie DVDs, video games, notebook PCs, personal digital assistants (PDAs), software, digital cameras and camcorders, DVD players,

[2] The products in the beers and cigarettes categories are highly regulated, which might skew the results (Besley & Rosen, 1999; Chen et al., 2008). We therefore do not discuss the results for these two categories.

[3] Dominick's data are available at http://research.chicagobooth.edu/marketing/databases/dominicks/stores.aspx. The site contains detailed information about the location of the stores, as well as a detailed description of the data files, product categories included, and other information. The site also discusses various measurement issues.

[4] When the sellers' Web sites were inaccessible or the price information was not available, instances of missing data occurred. The software agent used the following algorithm to address this issue. If 10% or more observations were missing for a product, then that series was excluded from the data altogether. If less than 10% of the data were missing, then the algorithm examined if the prices for the day before and the day after were the same. If they were the same, then the software agent automatically filled in the missing data with that price; otherwise it filled in the missing data with the price for the day after. Only 0.075% of the Internet data set was interpolated in this way because of missing observations, and thus missing data are unlikely to affect our results.

TABLE 1.—DESCRIPTIVE STATISTICS FOR THE DOMINICK'S PRICE DATA: STORES 8, 12, 122, AND 133

Category	Number of Observations	Number of Products	Mean Price	S.D.	Minimum Price	Maximum Price
Analgesics	174,132	599	$5.32	$2.51	$0.47	$23.69
Bath soap	31,859	492	3.31	1.76	0.47	18.99
Bathroom tissue	52,856	119	2.14	1.71	0.25	11.99
Beer	126,295	595	5.69	2.69	0.99	26.99
Bottled juice	204,967	460	2.24	0.97	0.32	8.00
Canned soup	251,505	400	1.15	0.49	0.23	5.00
Canned tuna	111,142	247	1.82	1.07	0.25	11.19
Cereals	213,771	447	3.17	0.78	0.29	7.49
Cheeses	312,455	594	2.43	1.12	0.10	11.50
Cigarettes	80,637	599	8.23	8.40	0.89	25.65
Cookies	355,388	1,018	2.11	0.63	0.25	8.79
Crackers	107,527	290	2.03	0.57	0.25	6.85
Dish detergent	101,077	270	2.37	0.92	0.39	7.00
Fabric softeners	108,050	308	2.85	1.47	0.10	9.99
Front-end candies	208,322	443	0.61	0.24	0.01	6.99
Frozen dinners	84,942	239	2.35	0.88	0.28	9.99
Frozen entrées	340,123	825	2.31	1.06	0.25	15.99
Frozen juices	109,916	160	1.36	0.43	0.22	5.00
Grooming products	244,043	1,237	2.95	1.39	0.49	11.29
Laundry detergents	156,156	556	5.67	3.24	0.39	24.49
Oatmeal	47,584	94	2.66	0.67	0.49	5.00
Paper towels	43,389	150	1.55	1.51	0.33	12.59
Refrigerated juices	102,221	213	2.20	0.88	0.39	7.05
Shampoos	306,053	2,615	3.06	1.87	0.27	29.99
Snack crackers	163,346	390	2.19	0.59	0.10	8.00
Soaps	94,722	313	2.60	1.58	0.25	9.99
Soft drinks	516,692	1,411	2.35	1.90	0.10	26.02
Toothbrushes	99,921	447	2.24	0.93	0.39	9.99
Toothpastes	161,038	574	2.49	0.97	0.31	10.99
Total	4,910,129	16,105	2.67	2.22	0.01	29.99

The data are weekly. The sampled stores belong to four price tiers: store 8, low price tier; store 12, high price tier; store 122, Cub fighter; and store 133, medium price tier.

PC monitors, and hard drives.[5] The Internet data contain over 2.5 million daily price observations. Table 2 presents descriptive statistics for the Internet data.

III. Evidence on the Popularity of 9-Ending and 99-Ending Prices

I asked the best economist I know, at least for such things—my wife, if she recalled a price not ending in a "9" at our local grocery store. "Not really," she said. "Maybe sometimes there are prices ending in a "5," but not really."

—Jurek Konieczny (2003)

We begin by presenting the results on the frequency distribution of price endings in the two data sets. In the analysis of Dominick's data, our focus was on 9¢ and 99¢ price endings because the overwhelming majority of the prices in retail grocery stores were well below $10.00 during the study period.[6] In the Internet data, the price ranges were different: from a minimum of $3.99 to a maximum of $6,000.00, with the average prices in different categories spanning $13.46 to $1,666.68 in the study period. The wider price range in the Internet data enables us to study not only 9¢ and 99¢ price endings, but also other 9-ending prices in both the cents and the dollars digits, including $9, $9.99, $99, and $99.99.

In figure 1, we report the frequency distribution of the last digit of the prices in Dominick's data. If a digit's appearance as a price ending was random, then we should have seen 10% of the prices ending with each digit. As the figure indicates, however, about 69% of the prices ended

[5] Product categories were selected based on their popularity on the Internet. The products in these categories were sold by a large number of stores. For example, in the category of digital cameras, the Canon-EOS Digital Rebel XT was sold by 63 stores. Our selection of products was random. For example, in the category of movie DVDs, we chose products from multiple subcategories (for example, action, drama, comedy). Similarly, in the music CDs category, we chose from many different subcategories (for example, blues, jazz, country). However, in some categories (such as notebook PCs and hard drives), we included all of the available products. In other categories (DVD players, digital cameras, PC monitors, software), we randomly chose products from all of the subcategories. For example, in the DVD players category, we chose half of the products from among standard DVD players, with the other half from the more expensive DVD/VCR combo players. In the digital cameras and camcorders categories, we chose half from regular digital cameras and the other half from digital camcorders. For PC monitors, we chose half from CRTs and flat CRT, and the other half from LCDs and TFTs. In the software category, we chose products from multiple genres, such as educational software, operating systems, programming software, and utility software. Similarly, for video games, we included multiple genres (adventure, action, sports). See figures R8a to R8j in the supplementary appendix for sample price series from our Internet data set.

[6] Indeed, according to Dutta et al. (1999), the average price of an item in large U.S. supermarket chains during 1991–1992 was about $1.70. Bergen et al. (2008) have noted that the figure increased to $2.08 by 2001. In our four-store sample, the average price is $2.67. See table 1.

TABLE 2.—DESCRIPTIVE STATISTICS FOR THE INTERNET PRICE DATA

Category	Number of Observations	Number of Products	Number of Retailers	Mean Price	S.D.	Minimum Price	Maximum Price
Music CDs	302,914	46	15	$13.46	$3.50	$3.99	$26.98
Movie DVDs	447,519	49	22	27.42	26.70	4.95	144.99
Video games	244,625	49	38	30.83	12.57	4.90	57.99
Software	382,297	48	83	294.07	417.60	4.95	5,695.00
Hard drives	263,244	46	73	330.67	556.29	39.00	3,670.98
PDAs	148,731	45	92	346.60	193.24	32.99	956.95
DVD players	220,236	49	104	369.51	247.75	57.99	1,489.00
PC monitors	319,369	51	87	682.89	659.13	85.78	3,010.41
Digital cameras	247,917	46	143	760.12	688.76	175.95	6,000.00
Notebook PCs	79,386	45	45	1,666.68	475.80	699.00	3,199.00
Total	**2,656,238**	**474**	**293**	**337.06**	**536.13**	**3.99**	**6,000.00**

The table covers 743 daily price observations from March 26, 2003, to April 15, 2005, from 293 Internet retailers for 474 products. The retailers have many different product categories (for example, Amazon.com sells books, CDs, DVDs, computer products, electronics, and so on). Consequently, the sum of the number of retailers in each product category will not necessarily be consistent with the total number of stores in all product categories. In addition, some retailers do not carry all products (in our sample, Amazon has 15 music CDs while Barnes & Noble has 20). Also, the length of individual products' price time series varies due to different life cycle of products. Thus, the number of observations in the music CDs category, for example, 302,914, is less than total available combinations ($46 \times 15 \times 743 = 512{,}670$).

FIGURE 1.—FREQUENCY DISTRIBUTION OF THE LAST DIGIT IN THE DOMINICK'S DATA, REGULAR PRICES: STORES 8, 12, 122, AND 133

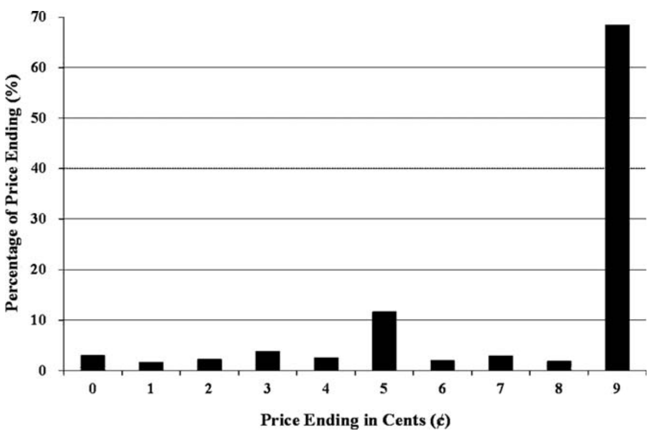


FIGURE 2.—FREQUENCY DISTRIBUTION OF THE LAST TWO DIGITS IN THE DOMINICK'S DATA, REGULAR PRICES: STORES 8, 12, 122, AND 133

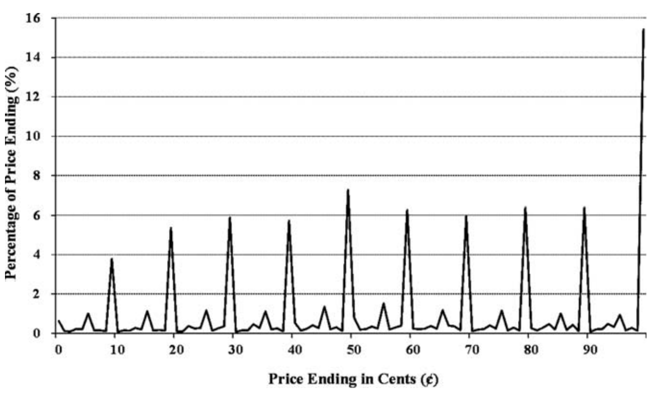
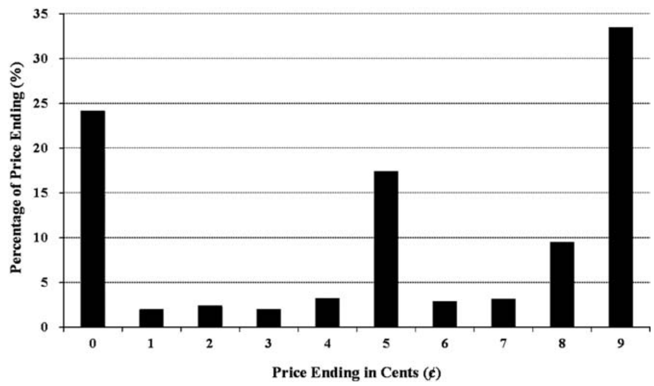


FIGURE 3.—FREQUENCY DISTRIBUTION OF THE LAST DIGIT IN THE INTERNET DATA



with a 9. The next most popular ending was 5, accounting for only 12% of all price endings. Only a small proportion of the prices ended with other digits.

Next, we consider the frequency distribution of the last two digits. With two digits, there are 100 possible endings, 00¢, 01¢, . . . , 98¢, and 99¢. Thus, with a random distribution, the probability of each ending should be only 1%. According to figure 2, however, most prices ended with either 09¢, 19¢, . . . , or 99¢. This is not surprising since 9 was the dominant single-digit ending. But of these, more than 15% of the prices ended with 99¢. In contrast, only about 4% to 6% of the prices ended with 09¢, 19¢, . . . , and 89¢.

Figure 3 displays the frequency distribution of the last digit in the Internet data. We can see that 9 was the most popular terminal digit (33.4%), followed by 0 (24.1%), and 5 (17.4%). The frequency distribution of the last two digits, shown in Figure 4, exhibits a similar pattern, with 99¢ as the most popular price ending (26.7%), followed by 00¢ (20.3%), 95¢ (13.8%), and 98¢ (4.8%).

The Internet data set also includes some high-price product categories, which allowed us to examine price endings in dollar digits as well. In figure 5, therefore, we present the frequency distribution of the last dollar digit in the Internet data. According to the figure, 9 was the most popular ending for the dollar digit, with $9 price endings overrepresented with 36.1%, followed by $4 price endings with 9.9%, and $5 price endings with 9.2%. The popularity of $4 and $5 ending prices stems from the fact that the actual prices in the low-price product categories (music CDs, movie DVDs, and video games) often are in the $10 to $15 range. This

FIGURE 4.—FREQUENCY DISTRIBUTION OF THE LAST TWO DIGITS IN THE INTERNET DATA

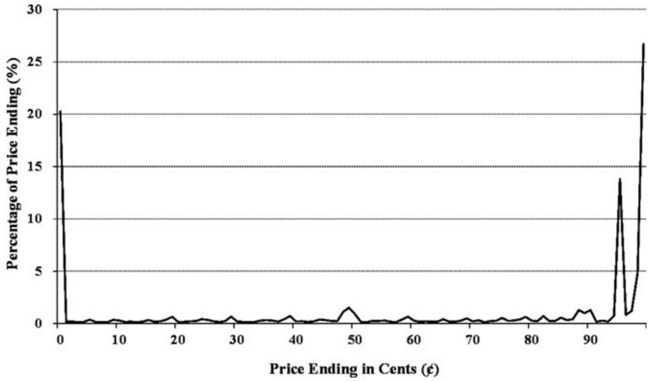


FIGURE 6.—FREQUENCY DISTRIBUTION OF THE LAST TWO DOLLAR DIGITS IN THE INTERNET DATA

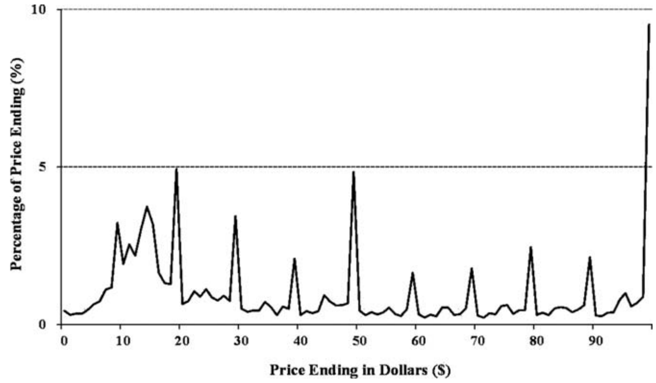


FIGURE 5.—FREQUENCY DISTRIBUTION OF THE LAST DOLLAR DIGIT IN THE INTERNET DATA

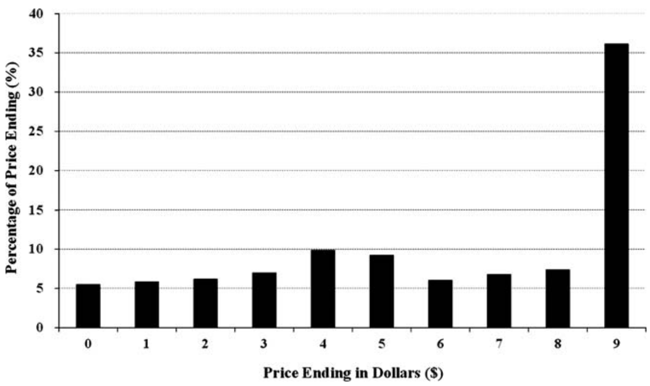


TABLE 3.—TOP TEN HIGHEST FREQUENCIES IN THE INTERNET DATA

Rank	Last Three Digits of Price Endings	Last Four Digits of Price Endings
1	$**9.99** (13.17%)	$**99.99** (3.47%)
2	**9.00** (9.98%)	**99.00** (3.46%)
3	**9.95** (4.86%)	**19.99** (2.16%)
4	4.99 (3.24%)	49.99 (2.00%)
5	5.00 (2.48%)	29.99 (1.55%)
6	2.99 (1.46%)	49.00 (1.43%)
7	8.95 (1.45%)	14.99 (1.40%)
8	8.00 (1.44%)	99.95 (1.09%)
9	7.99 (1.43%)	09.99 (0.97%)
10	4.95 (1.42%)	79.00 (0.87%)

The figures in each column are ordered from the most frequent to the least frequent. Prices in bold in the first three rows indicate that they are in the top three most frequent in each category.

explains the irregular behavior of the plot in figure 5 in the $10 to $15 range.

A similar pattern emerged for the last two dollar digits, shown in figure 6. Not surprisingly, the last two dollar digits of most prices contained 9 also, such as $99, $89, and $09. But more prices ended with $99 than any other two dollar digit endings. Moreover, almost 10% ended with $99 among the 100 possible dollar endings of $0 through $99.

We also examined the frequency distribution of the last three digits of prices in the Internet data. According to table 3 (first column), among the 1,000 possible endings, $9.99 was the most popular ending for the last three digits (13.2%), followed by $9 (10.0%), and $9.95 (4.9%). When we examined the last four digits of the prices (second column) among the 10,000 possible endings, $99.99 was the most popular ending (3.47%), followed by $99 (3.46%), and $19.99 (2.16%).

To summarize, in both data sets, 9 was the most popular terminal digit overall. But the popularity of 9 was not limited to the penny digit. It was popular in the dime, dollar, and ten-dollar digits too. The fact that our data include a variety of products with wide-ranging prices and different retail formats further underscores the popularity of 9 and 99 as a terminal cent and dollar digits.

IV. Frequency Distribution of Price Changes

Having documented the dominance of price endings of 9 and 99 as the terminal digits in both data sets, we next assessed the extent to which the specific price points 9 and 99 may be contributing to the retail price rigidity. To characterize the price change dynamics, we conducted a 10-state Markov chain analysis for price changes that affect one digit of a price (the penny digit and the dollar digit), and a 100-state Markov chain analysis for price changes that affect two digits of a price (the penny and the dime digits, and the dollar and the 10-dollar digits).

Table 4 displays the 10-state transition probability matrix for the penny digit for the Dominick's data at the four sampled stores. For ease of interpretation, the figures in the matrix (as well as in the remaining matrices) have been normalized, so that the probabilities in all rows and columns combined add up to 1. Considering all 100 possible transition probabilities, it is clear that 9¢-ending prices are the most persistent: 37.87% of the 9¢-ending prices preserve the 9¢-ending after the change. Moreover, when non-9¢-ending prices change, they most often end up with a 9¢ ending than with any other ending. Considering the diagonal elements of the matrix, after 9¢-ending prices, 5¢-ending prices seem to be the second most persistent, with a transition probability of 0.84%, followed by 0¢-ending prices,

TABLE 4.—TRANSITION PROBABILITY MATRIX CONDITIONAL ON A PRICE CHANGE FOR A TEN-STATE MARKOV CHAIN: DOMINICK'S DATA, STORES 8, 12, 122, AND 133, REGULAR PRICES ONLY, FOR THE PENNY DIGIT

Current Ending Digit (¢)	Next Period Ending Digit (¢)									
	0	1	2	3	4	5	6	7	8	9
0	**0.64**	0.25	0.29	0.31	0.33	0.79	0.26	0.23	0.16	3.68
1	0.26	0.14	0.18	0.21	0.14	0.44	0.14	0.13	0.09	2.98
2	0.25	0.13	0.15	0.18	0.19	0.36	0.18	0.15	0.09	1.81
3	0.28	0.20	0.16	0.33	0.22	0.47	0.20	0.24	0.15	2.47
4	0.30	0.12	0.17	0.18	0.29	0.40	0.23	0.17	0.11	2.93
5	0.72	0.30	0.32	0.42	0.33	**0.84**	0.43	0.49	0.26	3.81
6	0.26	0.15	0.18	0.21	0.26	0.37	0.20	0.29	0.14	2.15
7	0.23	0.14	0.15	0.28	0.21	0.41	0.25	0.24	0.13	2.17
8	0.15	0.10	0.11	0.14	0.14	0.29	0.13	0.13	0.12	1.43
9	3.40	1.58	1.45	1.88	2.34	3.15	1.85	1.77	0.85	**37.87**

Each cell contains the percentage of the price change compared to the total price change (1,374,142). The top three highest-transition probabilities on the matrix diagonal are indicated in bold.

TABLE 5.—TRANSITION PROBABILITY MATRIX CONDITIONAL ON A PRICE CHANGE FOR A TEN-STATE MARKOV CHAIN, INTERNET DATA, FOR THE PENNY DIGIT

Current Ending Digit (¢)	Next Period Ending Digit (¢)									
	0	1	2	3	4	5	6	7	8	9
0	**20.35**	0.35	0.35	0.34	0.33	1.40	0.39	0.38	0.52	1.69
1	0.32	0.39	0.33	0.32	0.34	0.29	0.30	0.28	0.30	0.40
2	0.40	0.33	0.47	0.34	0.34	0.27	0.24	0.31	0.34	0.32
3	0.34	0.29	0.32	0.47	0.33	0.35	0.32	0.30	0.41	0.43
4	0.37	0.34	0.37	0.31	0.66	0.52	0.40	0.38	0.37	0.87
5	1.45	0.33	0.30	0.34	0.48	**10.63**	0.45	0.34	0.53	2.04
6	0.34	0.29	0.31	0.34	0.43	0.48	0.86	0.41	0.30	0.66
7	0.39	0.27	0.27	0.37	0.36	0.32	0.33	0.66	0.49	0.58
8	0.54	0.33	0.30	0.37	0.44	0.58	0.41	0.48	2.95	1.21
9	1.54	0.42	0.42	0.48	0.87	2.19	0.54	0.56	1.47	**17.68**

Each cell contains the percentage of the price changes compared to the total number of price changes (41,034). The top three highest-transition probabilities on the matrix diagonal are indicated in bold.

TABLE 6.—TRANSITION PROBABILITY MATRIX CONDITIONAL ON A PRICE CHANGE FOR A TEN-STATE MARKOV CHAIN, INTERNET DATA, FOR THE DOLLAR DIGIT

Current Ending Digit ($)	Next Period Ending Digit ($)									
	0	1	2	3	4	5	6	7	8	9
0	1.58	0.85	0.45	0.40	0.42	0.43	0.35	0.41	0.68	1.38
1	0.98	2.18	1.06	0.49	0.40	0.35	0.33	0.40	0.43	0.97
2	0.58	1.19	1.72	1.01	0.76	0.56	0.34	0.32	0.48	1.12
3	0.46	0.67	1.23	1.99	1.12	0.65	0.50	0.42	0.51	1.00
4	0.55	0.49	0.87	1.30	**2.73**	1.32	0.69	0.65	0.62	1.98
5	0.49	0.44	0.61	0.90	1.50	**2.52**	1.01	0.67	0.54	1.45
6	0.36	0.37	0.42	0.52	0.88	1.15	1.47	0.86	0.64	1.04
7	0.33	0.30	0.41	0.48	0.79	0.79	1.14	1.27	0.88	1.22
8	0.49	0.39	0.38	0.57	0.56	0.72	0.71	1.11	1.73	1.79
9	1.08	0.83	0.81	0.91	1.98	1.56	1.25	1.47	2.09	**11.75**

Each cell contains the percentage of the price changes compared to the total number of price changes (41,034). The top three highest-transition probabilities on the matrix diagonal are indicated in bold.

with a transition probability of 0.64%. Overall, however, it seems that most of the transition dynamics takes place in the movement to and from 9¢-ending prices. Proportionally, there is very little transition from any particular non-9¢-ending prices to another non-9¢-ending price.

Table 5 displays the 10-state transition probability matrix for the penny digit for the Internet data. Focusing on the diagonal terms, we find that on the Internet, 0¢-ending prices are the most persistent, with a transition probability of 20.35%. Prices ending with 9¢ are the second most persistent, with a transition probability of 17.68%, followed by 5¢-ending prices with a transition probability of 10.63%.

Table 6 displays the 10-state transition probability matrix for the dollar digit for the Internet data. Focusing on the diagonal terms, we find that $9-ending prices are significantly more persistent than any other dollar-ending prices, with a transition probability of 11.75%. Prices ending with $4 are the second most persistent, with a transition probability of 2.73%, followed by $5-ending prices, with a transition probability of 2.52%. The persistence of the $4 and $5 endings stems from the fact that many price changes in the low-price product categories (music CDs, movie DVDs, and video games) take place in the penny and the dime digits.

TABLE 7.—TOP 25 TRANSITION PROBABILITIES CONDITIONAL ON A PRICE CHANGE FOR A 100-STATE MARKOV CHAIN: DOMINICK'S DATA, BY STORE, REGULAR PRICES ONLY, FOR THE PENNY AND DIME DIGITS

	Store 8			Store 12			Store 122			Store 133		
Rank	Current Ending	Next Ending	%	Current Ending	Next Ending	%	Current Ending	Next Ending	%	Current Ending	Next Ending	%
1	89	99	1.34	89	99	1.09	89	99	0.87	89	99	0.82
2	99	89	1.03	99	89	0.86	99	89	0.70	39	49	0.65
3	99	19	0.86	79	99	0.83	99	19	0.61	79	89	0.62
4	39	49	0.79	79	89	0.71	79	89	0.58	99	19	0.61
5	79	99	0.78	99	19	0.70	79	99	0.58	79	99	0.60
6	49	99	0.75	99	49	0.69	39	49	0.57	99	29	0.60
7	79	89	0.73	59	99	0.68	29	39	0.55	99	89	0.60
8	99	49	0.73	99	29	0.68	99	09	0.55	99	09	0.54
9	99	29	0.72	49	99	0.67	99	29	0.50	29	39	0.53
10	19	99	0.71	99	59	0.64	69	99	0.49	49	99	0.50
11	99	09	0.70	99	79	0.63	19	29	0.48	49	59	0.48
12	29	99	0.70	99	99	0.61	19	99	0.47	29	99	0.47
13	99	99	0.66	49	59	0.59	59	69	0.46	19	29	0.45
14	29	39	0.60	29	99	0.58	49	99	0.45	59	69	0.45
15	99	79	0.60	39	49	0.56	99	99	0.43	19	99	0.44
16	99	39	0.55	19	99	0.55	99	49	0.42	69	99	0.44
17	69	99	0.53	29	39	0.54	29	99	0.42	99	49	0.44
18	69	79	0.52	59	69	0.52	69	79	0.42	99	99	0.43
19	49	59	0.51	99	09	0.52	99	79	0.41	69	79	0.42
20	09	19	0.50	69	99	0.50	49	59	0.40	09	19	0.41
21	19	29	0.50	69	79	0.49	99	39	0.40	99	79	0.39
22	59	69	0.49	09	19	0.48	09	99	0.40	29	49	0.36
23	09	99	0.49	19	29	0.45	09	19	0.38	59	99	0.35
24	99	69	0.48	99	39	0.43	99	69	0.37	94	99	0.33
25	39	99	0.46	99	69	0.42	39	29	0.35	99	69	0.32

Comparing the figures presented in tables 5 and 6, it appears that the Internet retailers tend not to use the 9¢ ending proportionally as often. Instead, they use a $9 ending more often. Thus, the use of 9 as a terminal digit increases as we move from the penny and dime digits to the dollar and the ten-dollar digits. Below we offer more evidence consistent with this behavior.

We next report the results of 100-state Markov chain analysis for the terminal two digits of the price, for the penny and the dime digits for both data sets, and for the dollar and the ten-dollar digits for the Internet data. The resulting transition probability matrix, however, is 100×100. We therefore present only partial results of these analyses. The figures presented in these matrices are normalized as before, so that the probabilities in a table add up to 1.

Table 7 lists the top 25 transition probabilities for the penny and the dime digits at the four Dominick's stores. According to these figures, the most common transitions are from 89¢-ending prices to 99¢-ending prices, with the transition probabilities of 1.34%, 1.09%, 0.87%, and 0.82%, for stores 8, 12, 122, and 133, respectively. These probabilities seem quite high considering the fact that in the 100-state Markov chain, there are 10,000 possible transitions. The second most common movement is from a 99¢ ending to an 89¢ ending with the transition probability of 1.03%, 0.86%, and 0.70% at stores 8, 12, and 122, respectively. In store 133, the second most common movement is from a 39¢ ending to a 49¢ ending, with a transition probability of 0.65%. The third most common movement in stores 8 and 122 is from a 99¢ ending to a 19¢ ending with the transition probability of 0.86% and 0.61%, respectively; in store 12 from a 79¢ ending to a 99¢ ending with a transition probability of 0.83%, and in store 133 from a 79¢ ending to an 89¢ ending with a transition probability of 0.62%.

The transition from 99¢-ending prices to 99¢-ending prices comes only in the thirteenth, twelfth, fifteenth, and eighteenth places for stores 8, 12, 122, and 133, respectively, with the corresponding transition probabilities of 0.66%, 0.61%, 0.43%, and 0.43%. While these figures are quite high, it appears that other movements are more dominant than this particular transition. The reason for this, we believe, is that the average price in the Dominick's data is only $2.67. Moreover, in all but two product categories, analgesics and laundry detergents (beer and cigarette categories are not discussed, as mentioned in note 2), the average prices are $3.00 or less. A move from a 99¢-ending price to a 99¢-ending price therefore will result in a minimum price increase of 33% to 50% on average and a minimum price decrease of 25% to 33% on average. Changes of this magnitude seem fairly large, and therefore we suspect that they are not as frequent.

Table 8 lists the top 25 transition probabilities for the Internet data, with the penny and dime digits on the left-hand side and the dollar and the ten-dollar digits on the right-hand side. The top three transitions for the penny and dime digits are from 00¢-ending prices to 00¢-ending prices

TABLE 8.—TOP 25 TRANSITION PROBABILITIES CONDITIONAL ON A PRICE CHANGE FOR A 100-STATE MARKOV CHAIN, INTERNET DATA SET, FOR THE PENNY AND DIME DIGITS AND THE DOLLAR AND TEN-DOLLAR DIGITS

	Cents			Dollars		
Rank	Current Ending	Next Ending	%	Current Ending	Next Ending	%
1	00	00	18.36	14	14	1.47
2	99	99	11.89	11	11	1.36
3	95	95	8.83	15	15	1.28
4	98	98	1.13	09	09	1.23
5	00	99	0.89	13	13	1.16
6	99	00	0.85	99	99	1.01
7	99	95	0.72	12	12	0.80
8	00	95	0.66	10	10	0.67
9	99	98	0.64	08	08	0.63
10	99	49	0.62	14	15	0.59
11	49	99	0.62	16	16	0.58
12	95	00	0.62	15	14	0.54
13	95	99	0.57	14	13	0.49
14	98	99	0.54	12	11	0.48
15	49	49	0.28	13	14	0.48
16	00	50	0.25	11	12	0.44
17	88	88	0.24	22	22	0.43
18	50	00	0.23	12	13	0.42
19	85	85	0.20	13	12	0.42
20	96	96	0.19	99	49	0.42
21	89	99	0.19	19	19	0.41
22	00	90	0.18	11	10	0.39
23	96	99	0.18	21	21	0.39
24	24	99	0.17	49	99	0.38
25	97	97	0.16	10	11	0.35

Total number of price changes = 41,034.

with a transition probability of 18.36%, from 99¢-ending prices to 99¢-ending prices with a transition probability of 11.89%, and from 95¢-ending prices to 95¢-ending prices with a transition probability of 8.83%. The top three transitions for the dollar and the 10-dollar digits are from \$14-ending prices to \$14-ending prices with a transition probability of 1.47%, from \$11-ending prices to \$11-ending prices with a transition probability of 1.36%, and from \$15-ending prices to \$15-ending prices with a transition probability of 1.28%. The transition from \$99-ending price to \$99-dollar ending price came in only sixth.

The frequent use of the \$11-, \$14-, and \$15-ending prices stems from the fact that in the low-priced product categories, which include the music CD, movie DVD, and video game categories, these are not just price endings; these are actual prices. In these categories, therefore, the most common price changes are in the penny and the dime digits, which leave the dollar and the ten-dollar digits unchanged.

This finding suggests that price change patterns likely differ between low-priced and high-priced product categories. To explore this possibility further, we separated the Internet data into two groups: (a) low-priced product categories, which include music CDs, movie DVDs, and video games, and (2) high-priced product categories, which include computer monitors, digital cameras, DVD players, hard drives, laptop computers, PDAs, and software.

The results of the analyses are reported in table 9. Beginning with the low-priced product categories, we find that for the penny and the dime digits, the most common transition is from the 99¢ ending to the 99¢ ending with a transition probability of 16.32%, followed by a movement from the 98¢ ending to the 98¢ ending with a transition probability of 1.80%, and a movement from 95¢-ending to the 95¢-ending with a transition probability of 1.75%. For the dollar and the 10-dollar digits, we find that \$14-, \$11-, and \$15-ending prices are the most popular with the transition probabilities of 4.03%, 3.72%, and 3.53%, respectively.

Next, moving to the high-priced product categories, we find that for the penny and the dime digits, the most common transition is from the 00¢ ending to the 00¢ ending with a transition probability of 28.59%, followed by a movement from the 95¢ ending to the 95¢-ending with a transition probability of 12.77%, and a movement from the 99¢ ending to the 99¢-ending with a transition probability of 9.42%. For the dollar and the 10-dollar digits, we find that the top three transition probabilities are from \$99-ending prices to \$99-ending prices with a transition probability of 1.51%, from \$99-ending prices to \$49-ending prices with a transition probability of 0.65%, and from \$49-ending prices to \$99-ending prices with a transition probability of 0.60%.

In sum, we find that for the low-priced product categories, price changes that keep the terminal digits at 9 are the most popular in the penny digit, the penny and dime digits, and the dollar digit. For the high-priced product categories, price changes that keep the terminal digits at 9 are the most popular in the dollar digit, and in the dollar and ten-dollar digits. These results suggest that the persistent use of 9-ending prices is more likely to occur in the rightmost digits for low-priced products but shift to the left as the products became more expensive. This is consistent with the finding that 99¢-to-99¢ transitions were less common in the Dominick's data set, which consists of mostly low-priced products.

V. The Effect of Price Points on Price Rigidity

To study the link between 9-ending prices and price rigidity more directly, we use a binomial logit model to estimate price change probabilities. Using the method of maximum likelihood, we estimated the parameters α, β, and γ of the following equation:

$$ln(q/(1-q)) = \alpha + \beta 9\_Ending_{jt} + \gamma Product_{jt} + \varepsilon_t, \quad (1)$$

where q is the probability of a price change and 9_Ending_{jt} is a 9-ending dummy variable. For the Dominick's data, we estimate two versions of the regression. In the first, the 9_Ending_{jt} dummy equals 1 if the price for product j at time t ends with 9¢ and 0 otherwise. In the second regression, the 9_Ending_{jt} dummy equals 1 if the price for product j at time t ends with 99¢ and 0 otherwise. For the Internet data, we estimate six versions of the regression, corresponding to the six different values of the 9_Ending_{jt} dummy variable for 9¢, 99¢, \$9, \$9.99, \$99, and \$99.99.

TABLE 9.—TOP 25 TRANSITION PROBABILITIES CONDITIONAL ON A PRICE CHANGE FOR A 100-STATE MARKOV CHAIN, BY PRICE LEVEL, INTERNET DATA, FOR THE PENNY AND DIME DIGITS AND THE DOLLAR AND TEN-DOLLAR DIGITS

	Cents						Dollars					
	Low-Priced Categories			High-Priced Categories			Low-Priced Categories			High-Priced Categories		
Rank	Current Ending	Next Ending	%	Current Ending	Next Ending	%	Current Ending	Next Ending	%	Current Ending	Next Ending	%
1	99	99	16.32	00	00	28.59	14	14	4.03	99	99	1.51
2	98	98	1.80	95	95	12.77	11	11	3.72	99	49	0.65
3	95	95	1.75	99	99	9.42	15	15	3.53	49	99	0.60
4	99	98	1.19	00	99	1.34	09	09	3.31	99	79	0.54
5	49	99	1.04	99	00	1.29	13	13	3.21	79	99	0.40
6	98	99	0.97	00	95	1.02	12	12	2.18	99	89	0.39
7	99	49	0.95	95	00	0.96	10	10	1.84	49	39	0.33
8	96	96	0.50	99	95	0.94	08	08	1.62	49	49	0.28
9	24	99	0.45	98	98	0.76	14	15	1.59	89	79	0.28
10	99	24	0.42	95	99	0.75	16	16	1.55	79	69	0.28
11	96	99	0.40	99	49	0.44	15	14	1.40	39	29	0.27
12	89	99	0.37	00	50	0.39	13	14	1.26	49	29	0.25
13	88	88	0.37	49	99	0.39	14	13	1.25	29	99	0.25
14	99	95	0.34	50	00	0.35	12	11	1.17	99	69	0.25
15	99	19	0.33	99	98	0.33	11	12	1.16	99	94	0.24
16	82	82	0.28	49	49	0.32	22	22	1.15	59	49	0.23
17	99	89	0.27	98	99	0.30	12	13	1.12	99	98	0.23
18	19	99	0.26	85	85	0.29	13	12	1.06	79	49	0.22
19	95	99	0.26	00	90	0.27	19	19	1.06	19	99	0.22
20	99	39	0.25	97	97	0.22	21	21	1.01	69	59	0.21
21	99	29	0.25	90	00	0.20	11	10	0.94	89	99	0.21
22	49	59	0.24	94	99	0.18	10	11	0.90	99	29	0.20
23	49	49	0.22	90	90	0.17	23	23	0.84	29	19	0.20
24	09	95	0.21	99	94	0.17	16	17	0.78	09	99	0.20
25	59	69	0.21	88	88	0.17	17	16	0.74	19	09	0.18

Low-priced categories include CDs, DVDs, and video games. High-priced categories include computer monitors, digital cameras, DVD players, hard drives, laptop computers, PDAs, and software.

$Product_{jt}$ represents a set of product-specific dummy variables based on universal product codes (UPCs) in the Dominick's data and other unique product identifiers in the Internet data. They permit us to account for product-specific effects. For example, products for which 9-ending prices are more common may tend to be more rigid.[7]

The estimation results for the Dominick's data are reported in table 10. In the table, we present the estimated coefficients of each dummy along with the corresponding odds ratios. For all 27 product categories, the coefficient estimates for the 9¢-ending dummy are negative (all p-values < 0.0001). The odds ratios, which equal $e^{Coefficient}$, are all smaller than 1, indicating that 9¢-ending prices are less likely to change than prices that do not end with 9¢. On average, prices that ended with 9¢ were 66% less likely to change than prices that did not end with 9¢.

We obtained similar results for the 99¢-ending prices. The coefficient estimates for the 99¢-ending dummy are all negative. For 25 of 27 categories, they are statistically significant, as shown on the right-hand panel in table 10. The odds ratios indicate that prices that ended with 99¢ were on average 43% less likely to change than prices that did not end with 99¢.

Next, we estimated the same logit regression model for the Internet data, using dummies for 9¢, 99¢, \$9, \$9.99, \$99, and \$99.99, in turn, as the independent variables. As with the Dominick's data set, we included product dummies to account for product-specific effects. The estimation results are reported in table 11. Similar to what we found with the Dominick's data set, 9-ending prices were less likely to change than other prices. Overall, 9¢-ending prices were 25%, 99¢-ending prices 36%, \$9-ending prices 36%, \$99-ending prices 55%, \$9.99-ending prices 45%, and \$99.99-ending prices 64% less likely to change than other prices. We obtained similar results for the individual product categories. In 96% (52 of 54 categories) of all possible cases in the category-level analyses, the effect of price endings of 9 on the probability of price changes was negative and significant.

Thus, prices seem to be "stuck" at endings of 9 and 99, making them more rigid: 9¢- and 99¢-ending prices at Dominick's as well as on the Internet are less likely to change than other prices. On the Internet, the findings hold also for prices ending of \$9, \$9.99, \$99, and \$99.99.

[7] In an earlier analysis, we ran the above regression without the product dummies and obtained similar results. When we correlated the proportion of 9-ending prices for each product category with the regression coefficient of the 9-dummy from this earlier analysis, we obtained a significantly negative correlation for the 9¢-ending prices, suggesting a possible presence of some product-specific effects. For the 99¢-ending prices, the correlation coefficient was positive but statistically insignificant. We chose to include the product dummies in the results we report here.

Table 10.—Results of the Logit Regression, Equation (1), Estimation for the Dominick's Data, Regular Prices, Stores 8, 12, 122, and 133

	9¢ Ending ($9\text{-}Ending_9 = 1$)		99¢ Ending ($9\text{-}Ending_{99} = 1$)	
Category	Coefficient	Odds Ratio	Coefficient	Odds Ratio
Analgesics	−1.4820	0.23	−0.3599	0.70
Bath soap	−1.6871	0.19	−0.7683	0.46
Bathroom tissues	−0.4763	0.62	*−0.0353*	*0.97*
Bottled juices	−0.7232	0.49	−0.4984	0.61
Canned soup	−0.4553	0.63	−0.6055	0.55
Canned tuna	−0.7692	0.46	−0.5518	0.58
Cereals	−0.5013	0.61	−0.3582	0.70
Cheeses	−1.7457	0.17	−1.1008	0.33
Cookies	−2.1156	0.12	−1.1052	0.33
Crackers	−1.8639	0.16	−0.9784	0.38
Dish detergent	−1.0433	0.35	−0.7082	0.49
Fabric softeners	−0.6951	0.50	−0.3909	0.68
Front-end candies	−0.8917	0.41	−1.5532	0.21
Frozen dinners	−1.3773	0.25	−0.6168	0.54
Frozen entrees	−1.1704	0.31	−0.6649	0.51
Frozen juices	−0.3795	0.68	*−0.0395*	*0.96*
Grooming products	−2.2234	0.11	−0.6918	0.50
Laundry detergents	−1.5275	0.22	−0.5607	0.57
Oatmeal	−1.0142	0.36	−0.2450	0.78
Paper towels	−0.6164	0.54	−0.7879	0.45
Refrigerated juices	−0.8902	0.41	−0.4119	0.66
Shampoos	−2.1695	0.11	−0.3264	0.72
Snack crackers	−1.9320	0.14	−0.8181	0.44
Soaps	−1.6669	0.19	−0.6347	0.53
Soft drinks	−3.1645	0.04	−0.6425	0.53
Toothbrushes	−0.9833	0.37	−0.5719	0.56
Toothpastes	−0.6796	0.51	−0.6291	0.53
Average		0.34		0.57

$9\text{-}Ending_j$ are dummy variables; they equal 1 if the price ends with 9 or 99, and 0 otherwise. All p-values < 0.0001, except for the coefficients in italics (bathroom tissues and frozen juices, for 99¢-ending dummy), for which $p > .10$. The average odds ratios reported in the last row of the table are the simple averages of the odds ratios for each product category.

VI. The Effect of Price Points on the Size of Price Change

> If pricing points inhibit price changes, then they might also be expected to affect the sizes of price increases. Specifically if prices that are at price points are fixed longer than other prices, then any subsequent price adjustments might be expected to be larger than average.
>
> —Anil Kashyap (1995, p. 267)

If 9-ending prices are less likely to change in comparison to non-9-ending prices, then the average size of change of 9-ending prices should be larger when they do change, in comparison to non-9-ending prices. This assumes that the cost of a price change is the same regardless of the price ending, which we believe is indeed the case according to the menu cost estimates of Ray et al. (2006), Zbaracki et al. (2004), Zbaracki, Bergen, and Levy (2007), and Dutta et al. (1999) for large U.S. supermarket and drugstore chains.

In table 12, we report the average size of price changes for 9-ending and non-9-ending prices for both data sets. In the table, we also report the corresponding results for the low quartile of the products in terms of the popularity of 9-ending prices. The goal of the latter analysis is to assess the possibility that the findings we are documenting in this section may be driven by the frequent use of 9-endings. By limiting the analysis to the low quartile of the products in terms of the use of 9-endings, we are offering the most conservative test for this hypothesis.

In the Dominick's data set, the average price change was 75¢ if the price ended with 9¢, in contrast to a 40¢ change when it did not end with 9¢, an 88% difference. The findings for the 99¢-ending prices are also consistent: the average price change was 91¢ if the price ended with 99¢, in contrast to a 55¢ change when it did not end with 99¢. This amounts to a 65% difference.

Similarly, when we focused on the low quartile of products in terms of the popularity of 9-ending prices, the average price change was 38¢ if the price ended with 9¢, in contrast to a 33¢ change when it did not end with 9¢, a 15% difference. For the 99¢-ending prices, the average price change was 49¢ if the price ended with 99¢, in contrast to a 34¢ change when it did not end with 99¢. This is a 44% difference.

With the Internet data, we considered prices ending with 9¢, 99¢, $9, $9.99, $99, and $99.99, again for the entire data set, as well as for the low quartile of products. When we considered the entire Internet data set, for the 9-ending prices, the average price changes were $15.54, $22.40, $32.13, $33.97, $66.15, and $63.04 for prices ending in 9¢, 99¢, $9, $9.99, $99, and $99.99, respectively. The corresponding non-9-ending average price changes were $18.07, $16.78, $12.83, $16.30, $15.20, and $16.88, respectively. In other words, the 9-ending price changes were higher than non-9-ending price changes by about −14%, 33%, 150%, 108%, 335%, and 273%, respectively. Only in one case (Notebook PCs, 9¢- versus non-9¢-endings), was the average 9-ending price change lower than the average non-9-ending price change. (See table R22 in the supplementary appendix.)

When we considered the low-quartile data, for 9-ending prices, the average price changes were $24.02, $27.78, $11.93, $22.47, $49.61, and $38.24 for prices ending in 9¢, 99¢, $9, $9.99, $99, and $99.99, respectively. The corresponding non-9-ending average price changes were $21.03, $20.76, $7.21, $7.38, $18.27, and $19.21, respectively. Thus, the 9-ending price changes for the low-quartile products were higher than non-9-ending price changes by about 14%, 34%, 65%, 204%, 172%, and 99%, respectively.

Thus, the average size of the 9-ending and 99-ending price changes systematically exceed the average size of the non-9-ending and non-99-ending price changes, respectively. The fact that the results are similar for the overall data and the products in the low quartile suggests that in terms of the 9¢ use, the difference is unlikely to be driven by product-specific effects that could simultaneously increase the prevalence of 9-ending prices and the magnitude of the price changes. If that were the case, we should not have observed larger price changes for 9-ending and 99-ending prices in the low quartile of products for which 9-ending prices are less common. These findings are consis-

TABLE 11.—RESULTS OF LOGIT REGRESSION, EQUATION (1), ESTIMATION FOR THE INTERNET DATA SET

Category	9¢ Endings	99¢ Endings	$9 Endings	$99 Endings	$9.99 Endings	$99.99 Endings
Music CDs	−0.0727***	−0.5463***	−0.0125***		−0.4430***	
	(0.9299)	(0.5791)	(0.9876)		(0.6421)	
Movie DVDs	−0.4716***	−0.5827***	−0.3551***		−0.9068***	
	(0.6240)	(0.5584)	(0.7011)		(0.4038)	
Video games	**0.1630*** **	**0.0729*** **	−0.3572***		−0.2807***	
	(1.1770)	**(1.0756)**	(0.6996)		(0.7553)	
Software	−0.3185***	−0.4998***	−0.5892***	−1.0831***	−0.8032***	−1.4014***
	(0.7272)	(0.6067)	(0.5548)	(0.3385)	(0.4479)	(0.2463)
PDAs	−0.1496***	−0.2253***	−0.4370***	−0.5944***	−0.4041***	−0.8986***
	(0.8611)	(0.7983)	(0.6460)	(0.5519)	(0.6676)	(0.4071)
Hard drives	−0.2276***	−0.2777***	−0.3368***	−0.3242***	−0.5197***	−0.6072***
	(0.7964)	(0.7575)	(0.7141)	(0.7231)	(0.5947)	(0.5449)
DVD players	−0.5161***	−0.5808***	−0.7455***	−0.5246***	−0.6718***	−0.6074***
	(0.5968)	(0.5595)	(0.4745)	(0.5918)	(0.5108)	(0.5448)
PC monitors	−0.1893***	−0.3734***	−0.5445***	−0.7598***	−0.7457***	−1.3102***
	(0.8275)	(0.6884)	(0.5801)	(0.4678)	(0.4744)	(0.2698)
Digital cameras	−0.3634***	−0.4199***	−0.4464***	−0.9363***	−0.5052***	−1.1454***
	(0.6953)	(0.6571)	(0.6339)	(0.3921)	(0.6034)	(0.3181)
Notebook PCs	−0.3583***	−0.5335***	−0.7383***	−0.5533***	−0.7014***	−0.7149***
	(0.6989)	(0.5865)	(0.4779)	(0.5750)	(0.4959)	(0.4892)
Total	−0.2800***	−0.4330***	−0.4378***	−0.7787***	−0.5841***	−1.0201***
	(0.7558)	(0.6486)	(0.6455)	(0.4590)	(0.5576)	(0.3606)

Each cell contains a coefficient and odds ratio in parentheses. Significance levels. ***< 0.01, **< 0.05, *< 0.10. The estimated coefficients in italics indicate unsupportive results.

TABLE 12.—COMPARING AVERAGE SIZE OF PRICE CHANGE BETWEEN 9- AND NON-9-ENDING PRICES: DOMINICK'S (REGULAR PRICES; STORES 8, 12, 122, AND 133) AND INTERNET

	All Products				Low Quartile of Products in Terms of Popularity of 9-Ending Prices			
	9-Endings	Non-9-Endings	*t*-Statistic	*p*-Value	9-Endings	Non-9-Endings	*t*-Statistic	*p*-Value
Dominick's								
9¢	$0.75	$0.40	934.87	.000	$0.38	$0.33	27.61	.000
99¢	0.91	0.55	721.24	.000	0.49	0.34	53.64	.000
Internet								
9¢	*15.54*	*18.07*	*−4.50*	*.000*	24.02	21.03	2.75	.006
99¢	22.40	16.78	5.55	.000	27.78	20.76	4.56	.000
$9	32.13	12.83	33.65	.000	11.93	7.21	5.67	.000
$9.99	33.97	16.30	17.34	.000	22.47	7.38	5.99	.000
$99	66.15	15.20	42.89	.000	49.61	18.27	8.56	.000
$99.99	63.04	16.88	19.93	.000	38.24	19.21	4.78	.000

tent with our predictions: since 9-ending and 99-ending prices are less likely to change, the average sizes of the changes of the 9-ending and 99-ending prices are systematically larger when they do change, in comparison to the non-9-ending and non-99-ending prices, respectively.

VII. Robustness

To explore the robustness of the findings, we conducted several additional analyses, many of them following the referees' comments and suggestions. The findings we have reported in this paper for the Dominick's data were based on the analysis of the price data from the chain's four stores. However, we also analyzed the data for each of the four sampled stores individually, as well as the chain's entire data set, which includes the price information from all 93 stores. In each case, we considered the data for all 27 categories combined, as well as for each individual product category. For the Internet data, in this paper we have primarily reported the results of the aggregate data analysis. However, most of the analyses were repeated for each product category. In general, the results of these additional analyses are similar to the results that we have reported. Below we offer some details about these additional analyses and the findings. More detailed presentation of these analyses and their findings are included in the supplementary appendix.

A. *Evidence on the Frequency Distribution of 9- and 99-Ending Prices*

We found that 9¢- and 99¢-ending prices were more popular than other endings for the Dominick's data (for all 93 stores combined) and at each one of the four individual stores sampled. At the category level, we found that 9¢-ending prices were more popular than other endings at all 27 product categories, while 99¢-ending prices were more popular than other endings in 23 of the 27 product categories.

For the Internet data, we found that 9¢-ending and 99¢-ending prices were more popular than other endings for four product categories, while the 0¢-ending was the most popular for the remaining six categories. For the dollar digit, 9-endings were more popular than other endings in eight of the ten categories. For the last two dollar digits, $99-ending prices were more popular than the other price-endings in six of the ten categories.[8]

We also considered the possibility that the use of 9- and 99-ending prices is related to sales volume. The analysis of 9- and 99-ending prices by sales volume, however, suggests no such systematic relationship. The results suggest that 9-ending prices are popular for products that have a large sales volume as well as those that have a small sales volume.

B. *Evidence on the Frequency Distribution of Price Changes*

Similar to the other results that we report in this paper, we found that for regular prices in each of the four Dominick's stores, as well as for all 93 stores combined and for all prices, 9-to-9 was the most popular price change. For example, 37.74% of the transition takes place from 9¢-ending to 9¢-ending prices. Transitions from 5¢-to-5¢ endings and from 0¢-to-0¢ endings occur only with 0.90% and 0.66% probabilities. The 9¢-ending prices are the most persistent if we consider the entire Dominick's data as well. The price change 99-to-99 is not the most popular one for any of the four stores, similar to the results reported earlier in the paper, but it is the most popular when all prices from all stores are considered. For the Dominick's data set, in all but one category (front-end candies), there were considerably more price changes that were multiples of dimes and dollars for 9-ending prices.

For the Internet data, in the low-priced product categories, we found considerably more price changes that were multiples of dimes and dollars for 9-ending prices. For high-priced product categories, we found more price changes that were multiples of $10 and $100 for 9-ending prices.

C. *Evidence on the Link between 9- and 99-Ending Prices and Price Rigidity*

We find a strong, positive link between price points and price rigidity at the level of the entire Dominick's chain, as well as at each one of the four sampled stores examined. Beginning with store 8, we find that the probability of a change of 9¢-ending and 99¢-ending prices are on average 60% and 28% lower than non-9¢-ending and non-99¢-ending prices, respectively. The result holds true for most product categories: overall, in 50 of the 54 cases (27 coefficients for the 9¢-ending dummy and 27 coefficients for the 99¢-ending dummy), the coefficient of the 9-ending dummy was negative. In 48 of these 50 cases, they were statistically significant. We found similar results for the remaining three stores. For example, at store 12, the estimated coefficient was negative in 51 of the 54 cases, with 48 of them being statistically significant. At store 122, the estimated coefficient was negative in 53 of the 54 cases, with 50 of them being statistically significant. At store 133, the estimated coefficient was negative in 53 of the 54 cases, with 51 of them being statistically significant. The findings for the entire Dominick's data set are even stronger: all 54 estimated coefficients were negative and statistically significant.

D. *Evidence on the Link between 9- and 99-Endings and the Size of Price Changes*

In the Dominick's data set, in 23 of the 27 categories, the average price change was higher for 9¢-ending than for non-9¢-ending prices. The findings that we obtained for the 99¢-ending prices are even stronger. In 26 categories (the exception is frozen entrees), the average change was higher for 99¢-ending than for non-99¢-ending prices. Similarly, when we focused on the low quartile of products in terms of the popularity of 9-ending prices, we found that in 21 categories, the average change was higher for 9¢-ending than for non-9¢-ending prices. For the 99¢-ending prices, the average price change in 25 categories was higher for the 99¢-ending than for non-99¢-ending prices.

With the Internet data, we considered prices ending with 9¢, 99¢, $9, $9.99, $99, and $99.99, again for the entire data set, as well as for the low quartile of products. For the entire data set, we find that the average price change was higher if the price ended with 9 in comparison to non-9 ending prices in 8, 9, 9, 9, 8, and 7 categories for 9¢, 99¢, $9, $9.99, $99, and $99.99 ending prices, respectively.[9] Thus, in 50 of the 56 cases, the average size of the price change was higher if the price ended with 9 in comparison to non-9-ending prices.

The results for the low quartile of products are similar. Specifically, we find that the average price change was higher if the price ended with 9 in comparison to non-9-ending prices in 7, 10, 9, 9, 6, and 6 categories for 9¢, 99¢, $9, $9.99, $99, and $99.99 ending prices, respectively.[10] Overall, in 47 of the 54 cases, the average size of the price change was higher if the price ended with 9 than with a non-9 digit.

VIII. Conclusion

To our knowledge, this is the first study that directly examines the effect of price points on price rigidity across a

[8] Three individual product categories with low average prices exhibited some variation in their price endings. For example, for the dollar digit, the $3, $4, and $5 price endings were the most common for CDs and DVDs. That is because the prices in these categories usually range between $13 and $16. Also, the $99 and $99.99 endings were not common in those two categories or the category of video games, because the average prices in these categories are less than $100. We therefore did not see frequent 9-endings for the dollar and ten-dollar digits in these categories.

[9] Two categories, music CDs and video games, contained no prices with a $99 endings.

[10] There were no music CDs, music DVDs or video games with $99- or $99.99-ending prices.

broad range of product categories, price levels, and retailers in the traditional retailed and the Internet-based selling formats, using data from the United States. We found that 9-ending prices were the most popular and were less likely to change compared to non-9-ending prices. Further, the most common price changes preserve the terminal digits at 9, and the size of the price changes was larger for these 9-ending prices than for non-9-ending prices. We also discovered a shift in this preservation of 9-ending prices with the price level: for more expensive product categories, we saw less frequent persistence of 9s in the penny and the dime digits, but more frequent persistence of 9s in the $1, $10, and $100 digits.

Overall, we find that for the Dominick's data, 9-ending prices are at least 43% to 66% less likely to change than non-9-ending prices. For the Internet data, these probabilities are in the range of 25% to 64%. These figures seem to us quite substantial. We conclude that 9-ending and 99-ending prices form a considerable barrier to price changes, offering direct evidence on the link between price points and price rigidity. Combining this with the robustness of the findings—occurring in both data sets, across a wide range of product categories with a wide range of prices, products, retail formats, and retailers—suggests that price points might be substantial enough to have macro implications. This is reinforced by the finding that the use of 9s shifts leftward as the products' average price increases, which suggests that the phenomenon of 9-ending prices' rigidity may exist in markets for other goods and services in more expensive product categories where the use of 9-endings in $1, $10, $100 digits, and so on, is quite common. These include prices of the goods sold at department stores such as clothes, shoes, fragrances, jewelry, and high-tech equipment, as well as other high-priced products and services, such as musical instruments, furniture, cars, home appliances, hotels, air travel, car rentals, and even pricing of homes and apartments. Taken together, these goods and services comprise a substantial proportion of the aggregate consumption and thus may have a considerable economic significance.

The use of 9-ending prices seems to be relevant in the context of public policy issues as well. For example, the use of 9-ending prices is often debated in countries where low-denomination coins have been abolished. When small denomination coins are no longer used, transactions involving small changes must rely on rounding, as is the case in Israel, Hungary, and Singapore. In Israel, for example, the 1-agora coin was abolished in 1991, and the 5-agora coin was eliminated in 2008. The law therefore requires that the final bills be rounded up (if it ends with 5-agora to 9-agora) or down (if it ends with 1-agora to 4-agora) to the nearest 10-agora. It turns out, however, that the Israeli retailers use 9-ending prices extensively, which irritates consumers, who claim that 9-ending prices are unethical given the absence of the 1-agora coin. The Israeli Parliament has twice rejected a proposed law that would outlaw the use of 9-ending prices.[11] This may extend to other countries soon. For example, dropping the smallest currency unit has been a recent topic of debate in the United States, Canada, and Europe.[12] Australia stopped issuing 1¢ and 2¢ coins in 1989. New Zealand ceased issuing the 1¢ and 2¢ coins in 1989. Denmark stopped issuing the 5 and 10 ores in 1989. The Dutch eliminated the 1¢ of the guilder in 1980 and ceased issuing the 1¢ and 2¢ of Dutch euro coins in 2006. In Finland, the 1¢ and 2¢ of Finnish euro coins are no longer in general use. In 2008, Hungary eliminated the 1 and 2 forint coins. France, Norway, Britain, and Singapore have also eliminated low-denomination coins.

The common use of price points has also received considerable attention in some EU countries in the context of the conversion of prices from local currencies to the euro. The concern has been about the possibility that retailers may have acted opportunistically by rounding their prices upward after conversion to the euro in their attempt to preserve the price points. This appears to be true, for example, in the case of products that are sold through automated devices, such as soda and candy bar vending machines, parking meters, and coin-operated laundry machines (Bils & Klenow, 2004; Levy & Young, 2004; Campbell & Eden, 2010; Ehrmann, 2011; Hoffmann & Kurz-Kim, 2009).

In our data, 9 is the most popular terminal digit overall. The use of price points, however, seems to vary across countries with strong cultural characteristrcs. For example, Konieczny and Rumler (2007) and Konieczny and Skrzypacz (2010) note that 9-ending prices are particularly popular in the United States, Canada, Germany, and Belgium, but they are rare in Spain, Italy, Poland, and Hungary. According to Heeler and Nguyen (2001), in Chinese culture, numbers have special significance and symbolism. The number 8, for example, is associated with success.[13] They find that close to

[11] See, for example, http://www.globes.co.il/news/article.aspx?did=1000403091 (in Hebrew).

[12] In the July 19, 2001, issue of *USA Today*, L. Copland reported that "France, Spain and Britain quit producing low-denomination coins in recent decades because production costs kept going up while the coins' purchasing power went down." More recently, it has been reported that in many European countries that have adopted the euro, the public seems to be exhibiting resistance to the use of 1-cent and 2-cent denomination coins. This is due to the inconvenience their use entails. In the March 22, 2002 issue of the *International Herald Tribune* (Tel-Aviv Edition), E. Pfanner suggested that these coins are "small, nearly valueless—and a nuisance to millions of Europeans. The tiny denominations of the 1-cent and 2-cent euro coins are annoying shoppers and disrupting business from Paris to Milan." According to the *USA Today* report, in 2001, Rep. Jim Kolbe (R-Arizona) introduced the Legal Tender Modernization Act, to make the U.S. penny obsolete. The bill was defeated. Previous attempts made in 1990 and 1996 also died in Congress.

[13] A recent *New York Times* report (Toy, 2010) lists numbers that have particular significance in some cultures. Even the sounds of the numbers can suggest good or bad luck. For example, the number 8 represents luck to Cantonese Chinese because it sounds like "multiply" or "get rich" (*fa* in Cantonese). In Japan, 8 also has great symbolic significance because the character for the number 8 looks like a mountain ("八"), and thus the number 8 signifies growth and prosperity. In Jewish culture, the number 18 has a special significance because numerically it is equivalent to *chai*, which means life, and therefore, donations made by Jews are often in multiples of 18. In Indian society, birth date is used to determine the person's lucky numbers based on Vedic astrology.

50% of restaurant menu prices sampled in Hong Kong had 8-endings, which they refer to as "happy endings." Also, a *Time Magazine* article (Rawe, 2004) reported that at the casino of the $240 million Sands Macao hotel in Macao, China, the slot machines' winning trios of 7s have been replaced with trios of 8s. Consistent with these observations, the opening ceremony of the Beijing Olympic Games, held in the Beijing National Stadium, began exactly at 08:08:08 P.M. on 8/8/2008.[14]

Knotek (2008, 2011) has focused on other types of pricing practices, especially the common use of round prices, which he terms "convenient prices" because their use reduces the amount of the change used in a transaction. Levy and Young (2004), reported that the nominal price of Coca-Cola was fixed for almost seventy years at 5¢, also a convenient price.

Future work might study such pricing practices across other products, industries, retailers, and countries to assess the generalizability of our findings and observations. Beyond documenting these facts, this study raises interesting questions concerning the importance of price points for monetary nonneutrality. For example, how much monetary nonneutrality could be generated by pricing points? How are pricing points determined? To answer these questions, one would need a monetary economy model with pricing points. These remain interesting avenues for future research.

We end by noting that the Internet provides a unique context for microlevel studies of price-setting behavior (Bergen, Kauffman, & Lee, 2005). The ability to access transaction price data using software agents has allowed us to explore pricing and price adjustment patterns at a low cost and with a previously unimaginable level of microeconomic detail. This approach also allows empirical research methods to take advantage of natural experiments in the real world (Kauffman & Wood, 2007, 2009). With the expanding retail activities on the Internet, and new techniques and tools that have become available, we expect such opportunities to increase in the future.

[14] The cultural importance of numbers is not limited to "happy endings." For example, according to Mirhadi (2000), when the Masquerade Tower was added to Hotel Rio in Las Vegas in 1997, the architects decided to skip the 40th to the 49th floors because the Arabic numeral "4" in Chinese sounds similar to the word *death*. The elevators in the building went directly from the 39th floor to the 50th floor. According to Toy (2010), in many residential and commercial buildings, the 13th floor is missing, skipping from the 12th floor to the 14th floor.

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