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journal homepage: www.elsevier.com/locate/jmonecoNot all price endings are created equal: Price points and asymmetric price rigidity[☆]Daniel Levy^{a,b,c,*}, Avichai Snir^d, Alex Gotler^e, Haipeng (Allan) Chen^f^a Department of Economics, Bar-Ilan University, Ramat-Gan 52900, Israel^b Department of Economics, Emory University, Atlanta, GA 30322, USA^c The Rimini Centre for Economic Analysis, Wilfrid Laurier University, Waterloo, ON, Canada^d Department of Banking & Finance, Netanya Academic College, Netanya 42365, Israel^e Department of Education and Psychology, Open University, Raanana 43107, Israel^f Gatton College of Business and Economics, University of Kentucky, Lexington, KY 40506, USA

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ABSTRACT

We document an asymmetry in the rigidity of 9-ending prices relative to non-9-ending prices. Consumers have difficulty noticing higher prices if they are 9-ending, or noticing price-increases if the new prices are 9-ending, because 9-endings are used as a signal for low prices. Price setters respond strategically to the consumer-heuristic by setting 9-ending prices more often after price-increases than after price-decreases. 9-ending prices, therefore, remain 9-ending more often after price-increases than after price-decreases, leading to asymmetric rigidity: 9-ending prices are more rigid upward than downward. These findings hold for both transaction-prices and regular-prices, and for both inflation and no-inflation periods.

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“If the prior price ended with 99 cents, there is a lower probability of a price change. The size of this effect is striking ... [although it] is generally not a central feature of price rigidity analysis and models. The magnitude of the effect that we report suggests that this feature of retail pricing deserves greater attention.”

Eric Anderson, Nir Jaimovich and Duncan Simester (2015, p. 820)

1. Introduction

Asymmetric price rigidity is important as it can lead to asymmetric effect of aggregate demand (Ball et al., 1988; Cover, 1992; DeLong and Summers, 1988), it has implications for optimal inflation rate (Ball and Mankiw, 1994), and it can explain inflationary effects of sectoral shocks that change relative prices (Ball and Mankiw, 1995).¹ Also, it can add a kink to the Phillips curve, leading to asymmetric output loss from negative-positive inflation surprises (Kuran, 1983). Therefore, as Ellingsen et al. (2006) emphasize, it is of interest to monetary policy makers.

We document a surprising form of price adjustment asymmetry, which existing theories cannot explain.² Using four different datasets (laboratory experiment data, a field study data, and retail price data from two countries) to study the behavior of both consumers and retailers, we offer several new observations about the way retail price information is processed and interpreted by consumers, and the systematic price setting patterns that strategic retailers follow in response.

We report the following findings on consumer behavior. In the lab, (1) consumers process price/number digit information left-to-right when the task requires low cognitive effort, but not when the task requires high cognitive effort. (2) They use 9-endings as a signal for low prices: in 4% of the cases where the bigger of the two prices compared was 9-ending participants wrongly identified the 9-ending prices as smaller. In the field study (a real setting), we find that (3) shoppers pay greater attention to the right-most and the left-most digits, than to the middle digits: they are 19–29% more likely to correctly notice a price change if the change occurs in the left-most or the right-most digit, relative to a change in a middle digit. (4) Shoppers are 11% less likely to notice a price increase if the new price (the price following the increase) ends with 9.

We report the following findings about retail price behavior. (5) 9-endings are 6% more likely to be observed following a price increase than a price decrease. (6) 9-ending prices are more rigid upward than downward. Specifically, they are 32% more rigid upward than non 9-ending prices, while they are only 12% more rigid downward than non 9-ending prices. (7) The average increase in 9-ending prices is 12% larger than the average decrease in 9-ending prices.

Our empirical strategy is as follows. First, focusing on consumers' behavior, we show that in both the lab experiment and the field study, consumers use 9-endings as a signal for low prices. Consumers are less likely to notice higher prices if they end with 9, and less likely to notice price increases if the new prices end with 9. We do not observe these effects in case of price decreases.

Second, we explore the retailers' pricing practices. We hypothesize that strategically minded retailers keep prices at 9-endings more often after price increases than after price decreases. Consequently, 9-ending prices are more rigid upward than downward because they are more likely to increase to higher 9-ending prices (i.e., price increases will usually occur in multiples of 10¢), but price decreases are less restricted, because they do not need to be multiples of 10¢.

We test these hypotheses using price data from a large US retail chain Dominick's, and find that 9-ending prices are indeed more common after price increases than after price decreases. Also, as we hypothesize, they are more rigid upward than downward. An analysis of the Entry-Level-Item CPI data from Israeli retail supermarket and drugstore chains yields similar results.

Recent studies find that what matters for the macroeconomy are regular prices, not sale prices (e.g., Anderson et al., 2017; Kehoe and Midrigan, 2015; Midrigan, 2011; Eichenbaum et al., 2011), and therefore it is important to distinguish between regular and sale prices. For that purpose, we examine whether the asymmetric rigidity of 9-ending prices that we document is due to 9-ending regular prices going down to non-9-ending sale prices. Because in Dominick's data 9-ending prices are more likely to be regular prices than sale prices, we check whether the asymmetry also holds when we exclude sale prices. We explore these questions by running some additional tests.

First, we use the Dominick's sales indicator dummy variable as a control, wherever relevant. Second, we re-estimate all the regressions using regular prices only, by excluding from the analyses all sale related price changes using Dominick's sales indicator dummy variable. Third, we repeat the analyses using the sale filter of Nakamura and Steinsson (2008, 2011). Fourth, we repeat these analyses for the inflation-period and no inflation-period samples. We find that all the main results we are reporting in the paper hold for both the transaction prices and regular prices, irrespective of the estimation method used, irrespective of the inflationary environment, and irrespective of the sale filter used to separate regular prices and transaction prices. Often, the effects we are documenting are in fact stronger for regular prices than for transaction prices.

¹ Asymmetric price adjustment has been documented for consumer products (Anderson et al 2015, McShane et al 2016, Peltzman 2000), processed food (Chen et al 2008, Ray et al 2006), manufacturing (Blinder et al 1998), deposit interest rate (Hannan and Berger 1991, Neumark and Sharpe 1992, Driscoll and Judson 2013), gasoline (Davis and Hamilton 2004), foreign exchange (Gopinath and Itskhoki 2010), and fruits/vegetables (Ward 1982), in the US, Canada, and European Union (Hall et al 2000, Álvarez et al 2006, Dhyne et al 2006, Amirault et al 2004, Levy and Smets 2010).

² Existing theories include menu cost with trend inflation (Tsiddon 1993, Ball and Mankiw 1994), menu cost with asymmetric shocks (Ball and Mankiw 1995), menu cost with channels of processing (Ray et al 2006), fair pricing (Rotemberg 2005, Anderson and Simester 2010, Chen et al. 2018), customer antagonization (Blinder et al 1998, Rotemberg 2005, Anderson and Simester 2010), consumer inattention to small price changes (Chen et al 2008), and inventories, market structure, market power, and capacity constraints (Peltzman 2000, Loy et al 2016, Antoniou et al 2017).

The paper is organized as follows. In [Section 2](#), we lay out the hypotheses. In [Section 3](#), we describe the data and the findings. In [Section 4](#), we check robustness. We conclude in [Section 5](#).

2. Testable hypotheses and empirical strategy

People process multi-digit number information from left to right. Thus, when comparing two numbers that differ in one digit, people are usually faster and more accurate, if the numbers differ in their left-most digits than in the middle or the right-most digits ([Pollock and Schwartz, 1984](#)). The literature extends this finding to prices by assuming that consumers process multi-digit price information from left to right ([Stiving and Winer, 1997](#)).³ However, there is also evidence that consumers use 9-endings as a signal for low prices, suggesting that at least when the right-most digit is 9, they process the right-most digit information ([Schindler, 2001, 2006](#)).⁴ We suggest that if consumers perceive 9-endings as a signal for low prices, then 9-endings might have a negative effect on the likelihood that consumers will notice a price increase.

Focusing first on the consumer side, we use a lab experiment to test the hypothesis that 9-endings do not affect number comparisons because the endings have no particular significance in processing numeric information, but they affect the comparison of prices because the use of 9-endings as a signal for low prices might interfere with the left-to-right numeric price information processing. We thus hypothesize that consumers will be less accurate in comparing two prices when the higher price is 9-ending, compared to the situation where the lower price is 9-ending.

Next, we use field data on price recall accuracy to test the hypothesis that consumers are less accurate in recalling a price increase when the new price is 9-ending. If they interpret 9-ending prices as low, then they might not notice that a 9-ending price has increased, compared to the previous week.

In light of our findings concerning the consumers' behavior, we next focus on retail price behavior. We start by testing the hypothesis that retailers might respond strategically to consumer heuristics by choosing 9-ending prices more often after price increases, to reduce the likelihood that consumers will notice the increases. In such situations, prices that end in 9 are likely to remain 9-ending even after price increases. Retailers are less likely, however, to set 9-ending prices after price cuts because they use other means to ensure that the cuts are noticed. Indeed, price cuts are often promoted by using sale or discount signs, end-of-the-isle displays, large and colorful price tags, newspaper inserts, and leaflets distributed in stores ([Nevo, 2002](#)). Therefore, 9-ending prices are more likely to decrease than to increase to non 9-ending prices. In other words, 9-endings will be more rigid than other endings upward but less so downward.

In the last step, we test the hypothesis that because 9-endings are more rigid upward than downward, 9-ending prices will also be more rigid upward than downward. Indeed, we show that the asymmetric rigidity of 9-endings translates into an asymmetric rigidity of 9-ending prices.

3. Data and econometric analyses

In this section, we discuss the four datasets that we have assembled for this study, and describe the results of their econometric analyses. We begin with a laboratory experiment.

3.1. Evidence from a laboratory experiment

We start by describing the setup and the structure of the experiments we conducted. That is followed by two sets of econometric analyses of the data that these experiments generated.

3.1.1. Experimental setting and design

The goal of the experiment is to examine the effect of 9-endings on the way individuals process price information, in price comparison situations. We run the experiment at the Texas A&M University with 206 undergraduate students, with a median age 20, 66% female, 21% shop once a month or less, 34%—once every 2 weeks, 35%—every week, and 10%—twice a week or more. On average, the participants needed less than 15 minutes to complete the comparison task.

We employed a $2 \times 2 \times 2 \times 3$ mixed experiment design with 2 types of stimuli (number, price), 2 levels of comparison difficulty (low, high), 2 numbers of digits (3-digits, 4-digits), and 4 locations for the different digit (none, left-most digit, middle digit, right-most digit). The first three factors are between-subjects, while the last factor is within-subjects.

The type of stimuli was manipulated as follows. In the number-comparison condition, two numbers were shown on the computer screen. The numbers were either the same or differed in one digit. Participants had to press A (L) on the computer keyboard if the left (right) number was larger, or the space bar if they were equal. One practice block was followed by four experiment blocks of 75 comparisons each, with 10% of the numbers ending with 9. Before each comparison, participants

³ For example, consumers might perceive 9-ending prices as lower if price information is processed from left to right, and consumers ignore the 9-endings. Then, a price such as \$2.99 might be perceived as \$2.9 or even as \$2, and thus cheaper than the actual price ([Thomas and Morwitz 2005](#)).

⁴ Another theory suggests that consumers process all digits in the price information but perceive a 9-ending price as a gain from the next round price. That is, \$2.99 is a gain of 1¢ from \$3, and is perceived as much cheaper than \$3.00 ([Schindler and Kirby 1997](#)), because of the disproportional impact of the 1¢ gain on consumers' perceptions ([Kahneman and Tversky 1979](#)). Also, 9-ending prices can signal low prices simply for the common belief that they are linked with sales ([Anderson and Simester 2003](#)).

saw an image of an abacus on the screen for 1000 ms, followed by another screen with a “+” sign for 500 ms. The number condition serves as a baseline, to understand how consumers compare prices.

To make the price- and number-conditions comparable, the prices were shown as 3- or 4-digit numbers, without the \$ sign. The only difference was in the instructions, which indicated price or number comparisons, and in the image shown, which in the price condition was a supermarket aisle rather than an abacus. Comparison difficulty was manipulated by asking participants to identify the smaller or the larger of two numbers/prices. The comparison difficulty differs because “smaller” is a marked while “larger” is an unmarked adjective.⁵ People need more time, and they make more mistakes, when they process marked adjectives such as shorter, duller, or worse, than their unmarked equivalents, taller, brighter, or better (Lachman et al., 1979). Thus, the task of identifying the smaller of two numbers/prices is cognitively more demanding than the task of identifying the larger of two numbers/prices. Since heuristics are often used in dealing with difficult tasks (Kahneman and Frederick, 2002), we expect to see more reliance on 9-endings as a signal for low prices, and thus more frequent errors associated with 9-ending prices, in the cognitively more difficult find-small price condition, than in the find-large price condition.

The number of digits was manipulated by asking participants to compare 3-digit or 4-digit numbers/prices, which is the range of many consumer goods’ prices (Bergen et al., 2008; Barsky et al., 2003). The within-subject factor for the different digit location was manipulated by showing two numbers/prices that either were the same or differed in exactly one digit, e.g., 3.45 and 3.75.

The participants were asked to respond as quickly and as accurately as possible.⁶ They were told that 10% of them would be selected at random and paid based on their performance. The amount of the payment was computed according to the formula, $\max\{[10 - 5(x-1) - E], \$0\}$, where x is the participant’s average response time per comparison (in seconds), and E is the number of incorrect responses. In other words, they could earn up to \$10 if they used 1 second or less on average to answer correctly all comparison questions. The payoff was cut by \$5 if their average response time per comparison exceeded 1 second, and by \$1 for every incorrect response. The 1-second threshold was set based on a pre-test, which showed that the participants needed an average of 1 second for a comparison. The average payment the participants ended up receiving was \$5.10. In the empirical analysis, we use the data obtained from the non-practice blocks only. In total, the lab experiments yielded 55,346 observations.

We find that the average response time in the lab experiment was 1.05 seconds, and 89% of the responses were correct. Also, we find that identifying the smaller number/price was indeed harder for participants. They needed, on average, 1067 ms (1027 ms) to identify the smaller (the larger) number/price ($t = 11.6$, $p < 0.01$). The identification of the smaller number/price also produced more mistakes than the larger number/price (15.4% vs. 7.4%, $z = 28.7$, $p < 0.01$).

3.1.2. The effect of 9-endings on the accuracy of price- and number-comparisons

We hypothesize above that participants use 9-endings as a signal for low prices, and therefore they are more likely to make a mistake in comparing prices (but not when comparing numbers) when one of the prices compared is 9-ending, than when neither of the prices is 9-ending.

The descriptive statistics are consistent with this hypothesis. In both the number and price treatments, participants are more likely to give a correct answer when none of the prices/numbers compared ends in 9. We find that the likelihood of giving a correct answer when none of the prices (numbers) is 9-ending is 89.34% (88.54%). When at least one of the prices (numbers) is 9-ending, the probability is 87.91% (87.79%). The difference is statistically significant in the price treatment ($z = 3.11$, $p < 0.01$), but not in the number treatment ($z = 1.59$, $p > 0.10$).

These descriptive statistics are suggestive. To test that these results are robust to the inclusion of various control variables, we estimate the following linear probability regression model:

$$\begin{aligned} \text{accurate}_{ij} = & \alpha + \beta_1 9\text{-ending}_{ij} + \beta_2 9\text{-ending}_{ij} \times \text{price-comparison}_{ij} + \gamma_1 \text{right-most}_{ij} \\ & + \gamma_2 \text{middle}_{ij} + \gamma_3 \text{left-most}_{ij} + X_{ij} \delta + \varphi_i + u_{ij} \end{aligned} \quad (1)$$

where the dependent variable, accurate_{ij} , is a dummy that equals 1 if participant i answered question j accurately, and 0 otherwise. 9-ending is a dummy which equals 1 if the right-most digit of at least one of the two numbers/prices compared is 9, and 0 otherwise. $\text{Right-most/middle/left-most}$ are three location dummies (1 if the numbers/prices compared differ in the right-most/middle/left-most digit respectively, and 0 otherwise). They control for the possibility that participants process the price/number information left-to-right and, therefore, they will make fewer mistakes when the prices/numbers compared differ in their left-most digits than in their right-most digits.

⁵ Cognitive psychologists classify words as more complex if they are marked (Lachman et al. 1979, p. 396). Marked words are “governed by more restrictions on their use, and are less salient semantically than unmarked terms... The pair of words good and bad...are not entirely symmetrical. Good can mean either very good or somewhat neutral; while bad must mean bad. Consider the questions, ‘How good is your physics class?’ and ‘How bad is your physics class?’ The latter question presumes the class is bad, while the former does not presume it is good.” Thus, “bad” is marked while “good” is unmarked. Other examples include above (unmarked) and below (marked), happy (unmarked) and unhappy (marked), honest (unmarked) and dishonest (marked), etc.

⁶ See Online Appendix A for the instructions that were given to the participants and for other details on the laboratory experiment.

Table 1
Probability of a correct answer – lab experiment.

	(1) All observations	(2) Equal prices	(3) Unequal prices
9-Ending	−0.001 (0.004)	−0.007 (0.007)	0.02 (0.015)
Price Comparison×9-Ending	−0.01 (0.005)**		
Bigger-9-Ending			−0.04 (0.016)**
Right-Most	−0.08 (0.022)***		
Middle	−0.05 (0.023)**		
Left-Most	−0.04 (0.020)*		
Constant	0.94 (0.028)***	0.97 (0.021)***	0.92 (0.033)***
N	55,346	5982	20,905
χ^2	196.2***	10.3	51.3***

The table reports estimation results of a linear model with random effects for the probability of a correct answer. The dependent variable is the *accurate* dummy (1 if the answer is correct, 0 otherwise). Its average equals 0.89. The independent variables are the dummies *9-ending* (1 if at least one of the prices compared ends in 9), *Price-comparison* (1 if participants had to compare prices), *Bigger 9-ending* (if the bigger of the two prices/numbers compared ends with 9), and location dummies *Right-most/Middle/Left-most* (1 if the two prices/numbers compared differed in their right-most/middle/left-most digits, respectively). Other controls are *Find-small* (1 if participants had to identify the smaller of the two prices/numbers), *3-digits* (1 if the prices/numbers compared were 3-digit), *0-ending* (1 if at least one of the prices/numbers compared ended in zero), *Female* (1 for women), *Low shopping frequency* (1 if the participant reported shopping once a month or less), all the interactions of *price-comparison*, *find-small* and *3-digits*, the interactions of the location dummies with *price-comparison* and with *find-small*, and the interaction of *low shopping frequency* and *price-comparison*. Column (1) uses all observations. Column (2) uses observations on equal prices. Column (3) uses observations on unequal prices. Standard errors, clustered at the participant level, are reported in parentheses.

* $p < 10\%$,

** $p < 5\%$, and

*** $p < 1\%$. See Table 1A in Online Appendix J for more details.

The matrix X includes further controls, ϕ is the participants' random effects, and u is the error term.⁷ The key coefficients are the coefficients of *9-ending* and the interaction of *9-ending* and *price comparison*. If 9-endings have an effect on the way consumers process price information but not on the way they process number information, then the coefficient of *9-ending* should be insignificant. That is because in the number condition, participants will not use 9-endings as a signal. In the price condition, however, we hypothesize that they use 9-endings as a signal and, consequently, the coefficient of the interaction of *9-ending* and *price comparison* should be negative. We report the econometric model estimation results in column (1) of Table 1.

We find that while the coefficient of *9-ending* is not significant ($\beta_1 = -0.001$, $p > 0.10$), the coefficient of its interaction with *price-comparison* is negative and significant ($\beta_2 = -0.01$, $p < 0.05$). Thus, the regression results are consistent with the findings we report using the descriptive statistics: in the number condition, 9-endings do not affect the likelihood of a correct response. In the price condition, however, 9-endings reduce the likelihood of a correct response by about 1%. Given that the percentage of correct responses in the price treatment is 89%, a 1% increase in the likelihood of making a mistake is not trivial, because it implies that when at least one of the prices is 9-ending, the likelihood of an error increases from 11% to 12%, an increase of 9%.

In both the number and the price treatments, when participants had to identify the *smaller* of the two numbers/prices compared, the likelihood of a correct response did not depend on the location of the different digit, whereas when participants had to identify the *larger* of the two numbers/prices, it did. Thus, when participants face more difficult tasks, they rely more on heuristics. We find that 9-endings serve as such a heuristic in the price condition.⁸

3.1.3. The effect of 9-endings on the accuracy of price-comparisons when the two prices differ

If 9-endings signal low prices, then they will more likely affect the response accuracy when they appear in the higher of the two prices compared. To test this, we split the price condition sample in two. Subsample 1 (2) includes the trials in which the prices compared are equal to (different from) each other. We estimate a separate model for each. We do not expect 9-endings to affect the comparison accuracy in subsample 1 because in this subsample, when one price ends with 9, the other price also ends with 9. In subsample 2, we expect that 9-endings will have a negative effect on the comparison accuracy when the bigger price ends with 9 but not when the smaller price ends with 9. In subsample 2, thus, we include

⁷ Controls include *price-comparison* (1 = price, 0 = number), *find-small* (1 = find-small, 0 = find-large), *3-digit* (1 = 3-digit, 0 = 4-digit), and interactions of the location dummies with *price-comparison* and *find-small*, to control for the possibility that different cognitive processes are used in comparing prices/numbers, or if the task is cognitively more demanding. Because 0 is another common price ending and might signal quality (Snir et al 2018), we include a *0-ending* dummy (1 = the right-most digit of at least one of the two numbers/prices compared is 0, and 0 otherwise), and its interaction with *price-comparison*, to see whether *0-ending* affects number/price comparisons differently. Other controls include *gender* (1 = female, 0 = male), *low-shopping-frequency* (1 = once a month or less, and 0 otherwise), and its interaction with *price-comparison* to see whether shopping frequency affects number/price comparison tasks differently, and *digit-difference* which equals the absolute value of the difference between the digits of the numbers/prices compared (Monroe and Lee 1999). For example the digit difference between 3.87 and 3.57 is $|8 - 5| = 3$.

⁸ Indeed, in Online Appendix J, Table 1D, we show that when we use a probit model to estimate the probability of a correct response, the estimation results suggest that the likelihood of a correct response in the number condition depends on the location of the different digit, but in the price condition, it does not.

in the regression a *bigger-9-ending* dummy (1 if the bigger price ends with 9, and 0 otherwise). If the participants use 9-endings as a signal for low prices, then the coefficient of *bigger-9-ending* will be negative. We include also all the controls as in Section 3.1.2, except the location dummies and their interactions because of a multicollinearity in subsample 1. Columns 2 and 3 in Table 1 report the estimation results.

In both subsamples, the coefficient of *9-ending* is not significant. Therefore, when prices are equal or when the smaller price ends with 9, 9-endings do not affect the comparison accuracy (subsample 1: $\beta = -0.007$, $p > 0.10$; subsample 2: $\beta = 0.02$, $p > 0.10$). In subsample 2, however, the coefficient of *bigger-9-ending* is negative and significant ($\beta = -0.04$, $p < 0.05$). Thus, if the bigger price is 9-ending, the participants are more likely to mistakenly think that it is smaller, compared to the situation where it ends with another digit, consistent with the hypothesis that consumers use 9-endings as a signal for low prices (Anderson and Simester, 2003; Schindler, 2006).

3.2. Evidence from a field study

The goal of the field study is to examine the effects of 9-endings in a real shopping setting, where the cognitive load and the mental effort exerted is likely to be higher than in the lab. We examine the effect of 9-endings on the likelihood of noticing price changes. If consumers interpret a 9-ending price as a low price, then they will be less likely to notice that a 9-ending price has increased.

We surveyed 365 Israeli consumers at three supermarkets in three cities. Consumers exiting the stores were shown a list of 52 items in 12 product categories (dairy products, fresh fruits and vegetables, salt, sugar, cooking oil, soft drinks, cooking and baking products, canned food, coffee and tea, frozen food, sweets, crackers, meat, and laundry detergent), and were asked to mark the items they have bought on their current and previous shopping trips. For each item they marked, they were asked to indicate whether in their opinion the price of the item had increased, decreased, or remained the same, in comparison to the same item's price last week.⁹

The average participant in our survey is 40 years old, shops once a week, and spends NIS175.00 per visit on average.¹⁰ 56% of the consumers sampled are women, and 23% are religious. The questionnaire took an average of 10 minutes to fill out. On average, each consumer responded to questions on 12.1 products listed, and 65.3% of the responses were accurate.¹¹

3.2.1. Consumers' recall accuracy in the entire data set

If 9-endings signal low prices, then consumers will be less accurate in noticing price changes when the new prices are 9-ending than when they are not. The descriptive statistics support this prediction: Consumers correctly recalled whether a price has increased, decreased, or remained unchanged in 74.15% of the cases when the price was not 9-ending, and in 62.55% of the cases when the price was 9-ending. The difference is statistically significant ($z = 8.2$, $p < 0.01$).

As a more formal test, we estimate the following linear probability regression model:

$$accurate_{ij} = \alpha + \beta_1 9-ending_{ij} + \gamma_1 right-most_{ij} + \gamma_2 middle_{ij} + \gamma_3 left-most_{ij} + X_{ij} \delta + \varphi_i + u_{ij} \quad (2)$$

where $accurate_{ij}$ is a dummy which equals 1 if consumer i correctly recalled the price change direction (increased/decreased/remained unchanged) of good j , and 0 otherwise. *9-ending* and the location dummies are defined above.¹² One of the controls included in the matrix X (see footnote 12) is the *previous week's price*, which controls for the possibility that consumers' accuracy varies with the price level. We report the model estimation results in column (1) of Table 2.

We find that when a price is 9-ending, consumers are about 7% less likely to correctly recall whether or not the price has increased/decreased/remained unchanged ($\beta_1 = -0.07$, $p < 0.01$). We also find that they are more likely to notice a price change if either the right-most ($\gamma_1 = 0.10$, $p < 0.01$) or the left-most ($\gamma_3 = 0.09$, $p < 0.01$) digit changes than if a middle digit ($\gamma_2 = -0.20$, $p < 0.01$) changes. *Previous week's price* is not statistically significant.

Consistent with the laboratory experiment results reported in Section 3.2.1, these findings suggest that when consumers face situations where the cognitive load and the mental effort needed are high, they do not process price information left-to-right, but rather, they process the left-most- and the right-most-digits before the middle one. Further, the difference between the coefficients of *9-ending* and *right-most* suggests that although a 9-ending cannot completely cancel out the positive effect that a change in the right-most digit has on consumers' recall accuracy of price changes ($F_{\beta_1 = -\gamma_1} = 45.5$, $p < 0.01$), it does reduce this effect considerably.

⁹ See Online Appendix B for the questionnaire we used in the field study.

¹⁰ The exchange rate at the time was NIS4.37 for \$1.

¹¹ A sample selection bias could be an issue here because we do not have the proportion, nor the socio-demographic information, of the participants who declined to participate in the survey. However, based on parameters such as age, education, etc., our sample seems reasonable representative of the populations of the cities, where we collected these survey data. See Online Appendix X for details on the consumers in our sample.

¹² Controls include *female* (1 = female, 0 = male), *religious* (1 for ultra-religious, and 0 otherwise), *academic-degree* (1 = college degree, and 0 otherwise), *frequent-consumer* (1 = more than once a week, and 0 otherwise), *large-expenditure* (1 = more than NIS300 per visit, and 0 otherwise), *age* (1 = 55y-old or older, and 0 otherwise), *the previous week's price*, absolute value of the *price-change*, *price-increase* (1 if the actual price has increased, and 0 otherwise), *price-decrease* (1 if the actual price has decreased, and 0 otherwise), and *0-ending* (1 if the actual price ends with 0, and 0 otherwise). We include dummies for (i) ultra-religious since they have low incomes and large families, and thus face tighter budget constraints, and for (ii) 55+ year olds because they are less accurate in recalling prices (Macé 2012). The findings we report are consistent with these observations.

Table 2
Probability of a correct answer – field study.

	All observations	Price increases		Price decreases	
	(1)	(2)	(3)	(4)	(5)
9-Ending	-0.07 (0.015)***	-0.11 (0.051)**		-0.01 (0.057)	
From 9 to 9			-0.05 (0.061)		-0.06 (0.080)
From other to 9			-0.22 (0.073)***		-0.01 (0.090)
From 9 to other			0.05 (0.074)		-0.09 (0.097)
Right-Most	0.10 (0.020)***	0.15 (0.039)***	0.16 (0.040)***	0.11 (0.045)**	0.11 (0.047)**
Middle	-0.20 (0.028)***	-0.08 (0.046)*	-0.12 (0.050)**	-0.45 (0.051)***	-0.44 (0.054)***
Left-Most	0.09 (0.025)***	0.11 (0.033)***	0.11 (0.032)***	-0.01 (0.037)	-0.01 (0.038)
Intercept	0.76 (0.030)***	0.28 (0.087)***	0.28 (0.091)***	0.42 (0.087)***	0.45 (0.095)***
N	6031	639	639	581	581
χ^2	640.0***	124.5***	135.3***	562.8***	560.7***

The table reports estimation results of linear models with random effects for the probability of a correct answer. The dependent variable is the *accurate* dummy (1 if the answer is correct and 0 otherwise). Its average equals 0.65. The independent variables are dummies *9-ending* (1 if at least one of the prices ends in 9), *From 9 to 9* (1 if both the previous and the current prices end in 9), *From other to 9* (1 if the previous price didn't end in 9 and the current one does), *From 9 to other* (1 if the previous price ended in 9 and the current one does not), and *Right-most/Middle/Left-most* (1 if the two prices/numbers compared differed in their left-most/middle/right-most digit). Regressions (2)–(5) also include the following controls: *Female* (1 for women), *Ultra-Religious* (1 if the consumer is orthodox), *Academic degree* (1 if the consumer has academic degree), *More than one trip a week* (1 if consumer reported making more than one shopping trip a week), *More than NIS 300/shopping trip* (1 if the consumer spends more than NIS300.00 (about \$70) per shopping trip on average), *Older than 55* (1 if 55 or older), *Price increase/decrease* (1 if the price increased/decreases relative to the previous week), *Previous price* (the price of the good in the previous week), and *Relative size of the price change* (the absolute percentage change in the price). Column (1) uses all observations. Columns (2) and (3) use only observations on price increases. Column (2) uses one dummy, *9-ending*, to control for 9-ending prices. Column (3) splits the *9-ending* dummy into three dummies (*from 9 to 9*, *from other to 9*, and *from 9 to other*). Columns (4) and (5) are similar to (2) and (3) but for price decreases. Standard errors, clustered at the participant level, are reported in parentheses.

* $p < 10\%$,

** $p < 5\%$, and

*** $p < 1\%$. See Table 2A in Online Appendix K for more details.

3.2.2. Consumers' recall accuracy of price increases vs. price decreases

In the lab experiment, we observed that 9-endings interfered with the price comparisons when the bigger price was 9-ending. Specifically, we found that 9-endings decreased the probability of identifying the bigger price but did not help in identifying the smaller price (Section 3.1.3). This suggests that 9-endings have a stronger effect on consumers' recall accuracy of price changes when the 9-ending appears in the bigger price. In other words, 9-endings have a stronger effect when the new price is 9-ending after a price increase than after a price decrease.

To test this hypothesis, we split the sample in two. Subsample 1 (2) includes the observations on price increases (price decreases). For each, we estimate a random-effect linear probability model of the likelihood that consumers correctly notice price changes. The dependent variable in subsample 1 (2) is a dummy which equals 1 if a consumer correctly noticed a price increase (a price decrease), and 0 otherwise. Using this specification, we re-estimate regression (2), using the full list of controls as in 3.2.1. We report the estimation results in columns (2) and (4) of Table 2.

The effect of *9-ending* is negative and significant in the regression of price increases ($\beta = -0.11$, $p < 0.05$), but is small and not significant in the regression of price decreases ($\beta = -0.01$, $p > 0.10$). Thus, the negative effect of 9-endings on the likelihood of correctly noticing a price change seems to be due to the 9-endings reducing the likelihood of noticing price increases. 9-endings, however, do not appear to have a significant effect on the likelihood of noticing price decreases.

3.2.3. Consumers' recall accuracy "from" and "to" 9-ending prices

To further understand the effects of 9-endings on consumers' ability to recall price changes, we break the *9-ending* dummy in regression (2) into three dummy variables: *from-9-to-9* (1 if a 9-ending price changed to a 9-ending price, and 0 otherwise), *from-9-to-other* (1 if a 9-ending price changed to a non 9-ending price, and 0 otherwise), and *from-other-to-9* (1 if a non 9-ending price changed to a 9-ending price, and 0 otherwise). With this specification, we estimate regression (2) with the full list of control variables as above, for price increases and price decreases separately.

If consumers use 9-endings as a signal for low prices, as our findings so far suggest, then 9-endings are more likely to reduce the likelihood that the consumers will notice a price change, if a given price increases from a non-9-ending price to a 9-ending price. We therefore hypothesize that in the sample of price increases, the coefficient of *from-other-to-9* dummy will be negative.

Similarly, because we find that for price decreases 9-endings do not have a significant effect on the likelihood of noticing price decreases, we expect that the coefficient estimates will not be significant for any of the 9-ending dummies that we include for price decreases in the regression equation. We report the model estimation results in columns (3) and (5) of Table 2.

For price increases, we find that, as we hypothesize, when a non 9-ending price changes to a 9-ending price, consumers are less likely to notice a price increase ($\beta = -0.22, p < 0.01$).¹³

For price decreases, we find that none of the three 9-ending dummy variables are significant, consistent with the results we report in Section 3.2.2. Our results therefore suggest that 9-endings have a negative effect on the recall of price increases, but not on the recall of price decreases.¹⁴

3.3. Evidence from a large U.S. supermarket chain

So far we have focused on the consumers' behavior with regard to 9-ending prices. Next, we consider the price-setters' behavior by analyzing the dynamic adjustment patterns of retail prices at a supermarket chain. Our lab experiment and field studies suggest that consumers are less likely to notice price increases if the new price ends with 9. For price decreases, however, we find that 9-endings do not affect the price recall accuracy. Retailers that act strategically, therefore, will have greater incentive to keep prices at 9-endings after price increases than after price decreases. This predicts asymmetry in the likelihood that 9-ending prices will change. Specifically, 9-ending prices will be more likely to increase if the shock that triggers it is large enough to merit a change that is a multiple of 10¢, but they will be less restricted in the case of price decreases.

To examine the asymmetry in the rigidity of 9-endings prices, we study price data from a large US retail supermarket chain Dominick's, operating over 130 stores in the greater Chicago area. The data contain 98,691,750 weekly price observations for 18,037 different products (UPCs – Universal Product Codes) in 29 product categories, during 1989–1997. We exclude the end-points and incomplete segments of the individual price series, leaving us with 81,982,683 observations. The average price in the sample is \$2.34, and 62% of the prices end with 9.¹⁵ There are a total of 20,839,462 prices changes, of which 52.5% are increases and 47.5% decreases, with the average price change of 43¢. For more details about these data, see Barsky et al. (2003).¹⁶

3.3.1. Transition probability analysis: asymmetric transition of 9-endings

Table 3 reports 10-state Markov chain transition probability matrix for price increases and decreases by the last digit, conditional on a price change, from starting last digit to ending last digit. The figures on the diagonals of the matrices suggest that 9-endings are more rigid than other digits, as the probability of a 9-ending to remain a 9-ending exceeds the probability that any other ending will remain unchanged. In addition, looking at the table rows, we see that when prices change, the new prices end with 9 more often than with any other digit.

The last columns of the two panels indicate that a larger share of the prices end with 9 after price increases than after price decreases. Moreover, there is a statistically significant higher probability for a 9-ending price to remain a 9-ending after a price increase than after a decrease, 61.65% vs 56.55% ($z = 174.0, p < 0.01$). Thus, new prices are more likely to end with 9 after price increases than after price decreases, confirming asymmetry in the 9-ending price rigidity.

3.3.2. Asymmetric rigidity of 9-endings

To further assess the asymmetry in the rigidity of 9-endings, we estimate a linear probability model of the likelihood that the new price, following a price change, ends with 9 by estimating:

$$\text{end-9}_{ijt} = \alpha + \beta_1 \text{price-decrease}_{ijt} + \beta_2 \text{Previous-9-Ending}_{ijt} + X_{ijt}\gamma + u_{ijt} \quad (3)$$

where end-9_{ijt} is a dummy variable which equals 1 if the new price of a good i in store j in week t ends with 9, and 0 otherwise. The key independent variable is *price decrease* dummy (1 = price decrease, and 0 otherwise). *Previous-9-ending* dummy (1 if the pre-change price is 9-ending, and 0 otherwise) controls for the rigidity of 9-endings.¹⁷ Table 4 reports the model estimation results.

The coefficient of *previous-9-ending* is positive ($\beta_2 = 0.09, p < 0.01$), suggesting that 9-endings are indeed rigid: 9-ending prices are 9% more likely to end with 9 than other endings following a price change. However, the coefficient of *price decrease* is negative and significant ($\beta_1 = -0.06, p < 0.01$), suggesting that we are 6% less likely to see 9-endings following a price decrease than a price increase. Therefore, the estimation results confirm the observation conveyed by the transition probability matrices: although 9-endings usually change to 9-endings, retailers are more likely to set a price at 9-ending following a price increase than a price decrease.

¹³ This could explain why retailers often use non 9-endings for discounted prices. If the discounted prices are not 9-ending but the regular price are, consumers are less likely to notice the bounce-back from the discounted price to the regular price.

¹⁴ A possible explanation is that price cuts are often promoted by other means such as end-of-the-aisle displays, sale and discount signs, larger and/or more colorful price tags, leaflets and newspaper inserts, etc., and consequently the effect of 9-endings is small.

¹⁵ In the full sample of Dominick's data with 98,691,750 observations, 69% of the prices are 9-ending (Levy et al 2011). Figure 2B in Online Appendix Z shows the frequency distribution of the last digit in our sample with 81,982,683 observations.

¹⁶ The Dominick's dataset can be downloaded from the website of the Department of Marketing at the Booth School of Business, at the University of Chicago: <http://research.chicagobooth.edu/marketing/databases/dominicks/index.aspx>.

¹⁷ Controls include *price level* (the price without the penny-digit), *price change* (the absolute difference between the post-change and pre-change prices), and fixed effects for the stores.

Table 3

10-State Markov chain transition probability matrix for price increases and decreases by last digit, conditional on a price change, from starting last digit to ending last digit, in percents – Dominick's.

A. Price increases										
To										
From	0	1	2	3	4	5	6	7	8	9
0	5.560	4.900	5.850	5.040	5.850	13.84	3.540	3.470	2.090	49.86
1	3.800	2.510	6.430	8.010	4.420	15.45	3.350	3.480	1.830	50.71
2	4.390	2.880	3.770	6.970	5.600	15.79	3.910	4.020	2.430	50.25
3	5.590	2.650	2.360	5.410	6.190	15.54	4.270	5.240	3.160	49.59
4	3.950	2.090	2.740	2.750	3.110	12.30	4.810	4.370	2.430	61.45
5	8.170	3.000	2.920	3.470	2.620	12.85	5.960	6.630	4.030	50.35
6	5.180	3.250	4.660	3.720	4.550	9.890	2.650	9.320	4.000	52.79
7	5.510	3.770	4.240	4.580	3.180	12.41	2.130	4.880	4.080	55.22
8	6.840	6.140	4.550	6.390	3.620	13.67	3.170	3.250	3.720	48.66
9	6.660	4.070	3.880	4.210	4.350	7.780	2.480	3.220	1.700	61.65
B. Price decreases										
To										
From	0	1	2	3	4	5	6	7	8	9
0	10.18	3.000	3.300	5.210	4.180	10.68	5.490	3.770	3.120	51.06
1	12.52	2.730	3.610	4.260	4.030	8.180	6.010	5.110	5.700	47.86
2	14.32	7.220	3.500	3.230	4.720	7.310	9.050	5.240	3.270	42.14
3	10.24	9.390	5.670	5.810	3.920	6.760	5.260	5.400	3.940	43.61
4	12.63	4.730	5.720	6.600	4.910	5.910	6.570	3.980	2.390	46.56
5	11.33	5.610	6.170	8.050	6.340	7.830	5.690	5.680	3.280	40.01
6	9.360	5.400	5.470	7.330	10.73	9.270	4.730	3.850	2.770	41.08
7	7.060	3.810	4.180	6.350	9.610	10.57	11.81	4.430	2.180	40.02
8	7.780	3.610	4.710	6.980	9.650	12.89	9.970	8.380	4.210	31.82
9	8.650	3.080	2.670	3.980	6.200	6.440	5.910	4.460	2.060	56.55

Table 4

Probability that a new price ends with 9 – Dominick's.

Price decrease	−0.06 (0.004)***
Previous 9-Ending	0.09 (0.005)***
Price level	0.02 (0.002)***
Price change	0.0008 (0.00004)***
Constant	0.43 (0.007)***
R ²	0.03
N	20,839,462

The table reports the results of a linear regression for the probability that a new price ends with 9, conditional on a price change. The dependent variable is a dummy that equals 1 if the post-change price is 9-ending and 0 otherwise. The average of the dependent variable is 0.54. *Price decrease* is a dummy that equals 1 if the price change is negative. *Previous-9-ending* is a dummy that equals 1 if the pre-change price was 9-ending. *Price level* is the price without the penny digit. *Price change* is the absolute value of the price change. The regression also includes the store dummies (not reported).

*** $p < 1\%$. Standard errors, clustered at the UPC level, are reported in parentheses.

3.3.3. Asymmetric rigidity of 9-ending prices

Recent studies find that *9-ending prices* are more rigid than other prices (Levy et al., 2011, Anderson et al., 2015, Knotek 2016). The findings we present above suggest an asymmetry in this rigidity. That is, we expect that 9-ending prices will be more rigid upward than other prices but not necessarily more rigid downward than other prices. We pose this hypothesis because if an increase from 9-ending prices to non 9-ending prices is likely to be noticed, then 9-ending prices themselves should be less likely to increase—they will increase only when the shock that triggers the price change is large enough to make it optimal to set a higher 9-ending price. Downwards, however, there could be smaller or no difference between 9-ending and non 9-ending prices, because 9-endings do not help consumers notice price decreases.

To test this hypothesis, we first look at the proportion of price increases and decreases in our data. Looking at increases, we find that 10.9% of all 9-ending prices and 17.5% of all non 9-ending prices increased. When we look at decreases, we find that 11.6% of all 9-ending prices and 12.9% of all non 9-ending prices decreased. Thus, although 9-endings change less often than other prices in both directions, the effect is much more pronounced for price increases (10.9% vs. 17.5%, or a 37.7% difference) than for price decreases (11.6% vs. 12.9%, or a 10.1% difference).

Table 5

Probability of price increases and decreases relative to the price remaining unchanged – Dominick's.

	Price decreases	Price increases
Previous 9-Ending	-0.17 (0.016)***	-0.44 (0.013)***
Absolute value of % change in wholesale price	8.26 (0.118)***	7.35 (0.113)***
Sale price indicator in previous week	0.35 (0.015)***	3.01 (0.015)***
Price level	-0.15 (0.011)***	0.08 (0.005)***
Constant	-1.62 (0.030)***	-3.00 (0.019)***
χ^2	151,654.2***	
N	81,734,333	

The table reports estimation results of a multinomial-logit probability model of a price decrease/increase relative to the prices remaining unchanged. The dependent variable is an index variable and equals 0/1/2 if the price remained unchanged/decreased/ increased. The controls are *Previous-9-ending* (1 if the price was 9-ending), *Absolute value of % change in wholesale price*, *Sale price indicator in previous week* (1 if it was on sale), and *Price level* (price minus the penny digit).

*** $p < 1\%$. Standard errors, clustered at the UPC level, are reported in parentheses.

Next, we estimate a multinomial-logit regression model of the probability that a price will increase, decrease, or remain unchanged:

$$P(\text{direction}-\Delta P_{ijt} = k) = \frac{\exp(\beta_k \text{previous-9-ending}_{ijt} + X_{ijt} \gamma_k)}{1 + \sum_{l=1}^2 \exp(\beta_l \text{previous-9-ending}_{ijt} + X_{ijt} \gamma_l)} \quad (4)$$

The dependent variable, $\text{direction}-\Delta P_{ijt}$, is an index variable, which attains the values $k = 0/1/2$ if the price of a good i in store j in week t has remained unchanged/decreased/increased, respectively. We include *previous-9-ending* dummy to control for the effect of 9-endings on price rigidity, expecting its effect on the likelihood of price increases to be negative but less so on the likelihood of price decreases.¹⁸ Table 5 reports the model estimation results.

The effects of *previous-9-ending* on price increases and decreases are both negative ($\beta_2 = -0.44$, $p < 0.01$, and $\beta_1 = -0.17$, $p < 0.01$, respectively), implying that 9-ending prices are more rigid than other prices. What is perhaps more important however, is that the difference in their magnitude is both large as well as statistically significant ($\chi^2 = 324.6$, $p < 0.001$), which confirms that 9-ending prices are more rigid upward than downward.

Indeed, setting all variables to their average values and setting all the dummy variables to zero, we find that changing a price from a non 9-ending to a 9-ending is associated with a cut in the likelihood of a price increase from 6% to 4.1%, a reduction of 32.6%. Changing the price from a non 9-ending to a 9-ending is associated with a cut in the likelihood of a price decrease from 14.6% to 12.9%, a reduction of 11.7%. These figures therefore imply that the effect of 9-endings on price increases is almost three times larger than their effect on price decreases.

3.3.4. Asymmetry in the size of price changes

If 9-ending prices are more rigid upward than downward, then we would expect that when they do increase, they will increase by more than when they decrease. That is, the average increase of 9-ending prices should be larger than their average decrease. We indeed find that the average increase of 9-ending prices is 25.8%, significantly larger than the average decrease, 18.8% ($t = 423.3$, $p < 0.01$). To test this formally, we estimate the following regression model:

$$\left| \% \text{price-change}_{ijt} \right| = \alpha + \beta_1 \text{previous-9-ending}_{ijt} + \beta_2 \text{previous-9-ending}_{ijt} \times \text{price-decrease}_{ijt} + X_{ijt} \gamma + u_{ijt} \quad (5)$$

where the dependent variable, $\% \text{price-change}_{ijt}$, is the percentage price change of a good i in store j in week t . The main independent variables are the *previous-9-ending* dummy, and its interaction with the *price decrease* dummy.¹⁹ Table 6 reports the model estimation results.

As expected, the coefficient of *previous-9-ending* is positive ($\beta = 0.05$, $p < 0.01$), while the coefficient of the interaction of *previous-9-ending* with *price decrease* is negative ($\beta = -0.07$, $p < 0.01$). Thus, consistent with the findings discussed above that 9-ending prices are more rigid upward than downward, we also find that when 9-ending prices increase, they increase by 5% more than the expected price change of non-9 ending prices. When 9-ending prices decrease, they decrease by 7% less than the expected price change of non-9 ending prices. The expected change when 9-ending prices increase is, therefore, $5\% + 7\% = 12\%$ larger than when 9-ending prices decrease. The difference is statistically significant ($F = 23.1$, $p < 0.01$).

¹⁸ Controls include the *absolute value of % change in wholesale price*, a dummy for *sale price in the previous week* (1 if the price was a sale price, and 0 otherwise) because sale prices are more likely to change than regular prices, *price level*, and store dummies. Some wholesale price changes were suspiciously large. We therefore drop 238,279 observations with wholesale price changes of 200% or more.

¹⁹ Controls are *price level*, the *absolute value of % change in the wholesale price*, dummies for *sale prices in the current and previous week*, and *store dummies*. The sale price dummies are included because both the drop to a sale price and the bounce-back, likely differ from other price changes. The wholesale price is included since retail price changes is likely to be correlated with it (Anderson et al 2017, McShane et al 2016). We again exclude the observations with wholesale price changes of 200% or more.

Table 6
The size of a 9-ending price change – Dominick's.

Previous 9-Ending	0.05 (0.003)***
Previous 9-Ending × Price-Decrease	−0.07 (0.003)***
Price Level	0.0005 (0.0009)
Absolute value of % change in wholesale price	0.55 (0.017)***
Sale price indicator in previous week	0.04 (0.002)***
Sale price indicator	0.002 (0.002)
Constant	0.13 (0.004)***
R ²	0.06
Number of observations	20,601,077

The table reports estimation results of a linear regression of the % price change, conditional on a price change. The dependent variable is the absolute % price change (average = 0.22). The independent variables are *previous-9-ending* (1 if the pre-change price was 9-ending), *price-decrease* (1 if the price change is negative), the *absolute value of the % change in the wholesale price*, *sale price indicator in previous/current week* (1 if the good was on sale in the previous/current week), and store dummies.

*** $p < 0.01\%$. Robust standard errors, clustered at the UPC level, are reported in parentheses.

3.3.5. 9-ending price increases and consumer inattention

An alternative explanation for our findings in the lab experiment and in the field study, is that consumers are inattentive to increases in 9-ending prices, if these tend to be small. Indeed, since processing price information is cognitively demanding and time-consuming, consumers could ignore price changes, if they expect these changes to be small (Banerjee and Mullainathan, 2008).

However, according to the data, the average absolute (percentage) price increase when the new price is 9-ending is \$0.46 (25.5%), which is larger than the average price increase when the new price is not 9-ending, \$0.34 (23.2%). The differences are statistically significant at 1%: for absolute price increases $t = 350$, and for % price increases $t = 58.1$.

As a further test, we check whether or not the price increase is smaller when the new price is 9-ending, in comparison to a situation where the new price ends with some other digit. For this purpose, we run the following linear regression model:

$$\text{price-increase}_{ijt} = \alpha + \beta 9\text{-ending}_{ijt} + X_{ijt}\gamma + u_i \quad (6)$$

where the dependent variable, $\text{price-increase}_{ijt}$, is the price-increase of a good i in store j in week t . The main independent variable is *9-ending*, which equals 1 if the price after the increase is 9-ending and 0 otherwise. The matrix of controls X includes fixed effects for the store, the year, and the UPC. We estimate this regression twice. In the first, *price-increase* is measured in absolute terms (dollars). In the second, *price increase* is measured in relative terms (percents).

The results (see Table 15A in Online Appendix T) show that in the regression of absolute price increase, the coefficient estimate of *9-ending* is 0.014 ($p < 0.01$). This suggests that when the new price is set at a 9-ending, the expected price increase is 1.4¢ larger than when the new price is set at a different ending. In the regression of relative price increases, the coefficient estimate of *9-ending* is 0.015 ($p < 0.01$), meaning that when the new price is set at a 9-ending, the expected price increase is 1.5% larger than when the new price is set at a different ending.

Thus, both regressions suggest that the price increase is larger when the new price (that is, the price following the increase) is set at a 9-ending, in comparison to the situation where the new price is set at some other ending. Therefore, consumers should not have any less incentive to pay attention to 9-ending price increases. To the contrary, they should be paying more attention to 9-ending price increases, which is counter to the above competing hypothesis.

3.4. Evidence from the Israeli supermarkets and drugstores

As a further test, we use Entry-Level-Item (ELI) supermarket and drugstore data collected by the Israeli Central Bureau of Statistics (CBS) for CPI compilation. Since the field data in Section 3.2 came from Israel, for robustness it is useful to show that the results that hold for the US data, hold for the Israeli data as well, which would suggest a broader relevance of our findings.

The CBS data cover the period from January 2002–December 2013, and include 190,807 monthly price observations for 11,313 different goods in 99 product categories. In addition, the data contain information on the type of the stores, and the district where the stores are located. The minimum price in the sample is NIS 0.45 (\$0.11) and maximum NIS 999.99 (\$250). The average price is NIS 22.83 (\$5.71), and the standard deviation is 55.07.

The share of 9-ending prices in the Israeli price data is 65.5%, which is similar to the proportion found in the Dominick's data, suggesting that 9-ending prices are as prevalent in Israel as in the US (Snir et al 2017).²⁰ The CBS data does not contain

²⁰ Figure 2A in Online Appendix Y shows the frequency distribution of the last digit of the prices in the Israeli supermarket and drugstore chains.

Table 7

10-State Markov Chain Transition Probability Matrix for Price Increases and Decreases by Last Digit Conditional on Price Change, From Starting Last Digit to Ending Last Digit, in percents – Israeli Supermarkets and Drugstores.

A. Price increases										
		To								
From	0	1	2	3	4	5	6	7	8	9
0	46.160	0.774	1.162	0.904	0.855	9.519	0.645	0.419	0.565	38.996
1	14.362	4.787	2.128	15.957	4.255	15.426	5.319	10.106	3.723	23.936
2	12.030	2.256	7.143	4.511	4.511	21.053	4.511	6.015	2.256	35.714
3	14.539	1.418	4.610	1.773	3.191	10.284	5.319	7.801	10.993	40.071
4	8.031	2.850	4.145	5.440	4.663	10.104	2.073	2.332	3.627	56.736
5	15.649	1.013	0.767	0.338	0.368	49.923	1.258	0.736	1.013	28.935
6	13.475	2.128	5.674	9.574	5.674	7.801	2.837	3.191	3.546	46.099
7	9.504	7.438	2.893	8.264	4.132	13.636	2.066	4.959	3.719	43.388
8	7.372	2.564	1.603	4.167	5.449	6.090	2.244	6.410	1.923	62.179
9	9.798	0.407	0.600	0.497	0.828	3.169	0.551	0.421	0.510	83.219
B. Price decreases										
		To								
From	0	1	2	3	4	5	6	7	8	9
0	50.276	0.212	0.212	0.127	0.191	7.958	0.191	0.255	0.233	40.344
1	41.284	6.422	0.917	1.835	3.670	3.670	1.835	4.587	1.835	33.945
2	32.824	7.634	4.580	4.580	3.053	4.580	0.763	4.580	2.290	35.115
3	28.571	8.844	2.041	5.442	5.442	8.163	4.082	2.041	0.680	34.694
4	23.214	4.167	3.571	2.976	9.524	1.786	2.381	1.190	1.190	50.000
5	17.586	0.449	0.987	0.987	1.211	55.182	0.583	0.404	0.314	22.297
6	20.979	1.399	7.692	8.392	3.497	14.685	4.895	1.399	4.196	32.867
7	21.849	5.042	4.202	2.521	7.563	16.807	3.361	4.202	0.000	34.454
8	28.906	0.781	1.563	3.125	1.563	10.938	13.281	4.688	6.250	28.906
9	12.841	0.154	0.154	0.291	0.725	2.730	0.434	0.346	0.769	81.558

information on wholesale prices or sales, and thus we cannot replicate the above tests exactly. We can nevertheless assess asymmetric rigidity of 9-ending prices by estimating the same type of regressions as we estimated above.

3.4.1. Transition probability analysis: asymmetric transition of 9-endings

Table 7 reports 10-state Markov chain transition probability matrix for price increases and decreases by the last digit, conditional on a price change. The figures on the diagonals suggest that the probability of a 9-ending to remain a 9-ending exceeds the probability that any other ending will remain unchanged. Thus, at the Israeli retail chains as at Dominick's in the U.S., 9-endings are more rigid than other endings.²¹ In addition, looking at the table rows, we see again that after a price change, the new price ends with 9 more often than with any other digit.

The last columns of the two panels of Table 7 indicate that a larger proportion of the prices end with 9 after price increases than after price decreases. In particular, the probability is higher for a 9-ending price to remain a 9-ending following an increase than following a decrease, 83.22% vs 81.56%. Moreover, this difference is statistically significant ($z=4.4$, $p < 0.01$). Thus, new prices at Israeli retail outlets are more likely to end with 9 after price increases than after price decreases, similar to the findings for Dominick's in the U.S., as discussed in Section 3.3.1.

3.4.2. Asymmetric rigidity of 9-endings

To assess the asymmetry in the rigidity of 9-endings more formally, we estimate the regression equation given in equation (3). The dependent variable is a dummy, which equals 1 if the new price ends with 9, and 0 otherwise. The main independent variable is *price-decrease*.²²

The estimation results reported in Table 8 show that the coefficient estimate of *previous-9-ending* is positive ($\beta_2 = 0.40$, $p < 0.01$), implying that 9-ending prices are 40% more likely to end at 9 than other endings after a price change. However, the coefficient estimate of price decrease ($\beta_1 = -0.03$, $p < 0.01$) is negative and significant. We thus conclude that in Israel, as in the US, we are more likely to see 9-endings following price increases than following price decreases.

3.4.3. Asymmetric rigidity of 9-ending prices

Looking first at the descriptive statistics, we find that the percentage of price increases (decreases) of 9-ending prices, 17.9% (14.6%), is larger than the percentage of price increases (decreases) when the price is not 9-ending, 17.3% (12.0%).

²¹ Figures 1A and 1B in Online Appendix Q show the probability that a price with a given end-digit will end with the same digit following a price increase and decrease, for Dominick's and for the Israeli supermarket and drugstore chains, respectively.

²² Controls include *previous-9-ending*, *price level*, absolute value of *price change*, and product *category* and *district* dummies.

Table 8
Probability that a new price ends with 9 – Israeli supermarkets and drugstores.

Price decrease	−0.03 (0.007)***
Previous 9-Ending	0.40 (0.012)***
Price level	−0.0002 (0.0003)
Price change	−0.00002 (0.0001)
Constant	0.33 (0.010)***
R ²	0.25
N	59,852

The table reports the estimation results of a linear regression for the probability that a new price ends in 9, conditional on a price change. The dependent variable is a dummy which equals 1 if the new price ends with 9, and 0 otherwise (average = 0.68). The controls are *Price decrease* (1 if a price change is negative), *Previous-9-ending* (1 if the pre-change price was 9-ending), *Price level* (price without the penny digit), the absolute value of *Price change*, and dummies for *product categories* and for *districts*.

*** $p < 0.01$. Robust standard errors, clustered at the product category level, are reported in parentheses.

Table 9
Probability of price increases and decreases relative to price remaining unchanged – Israeli supermarkets and drugstores.

	Price decreases	Price increases
Previous 9-Ending	−0.28 (0.017)***	−0.34 (0.015)***
Price level	−0.01 (0.001)***	0.003 (0.0003)***
Constant	−1.68 (0.087)***	−1.32 (0.061)***
χ^2	27,370.8***	
N	190,807	

The table reports the estimation results of a multinomial-logit regression of the probability of a price decrease/increase relative to the price remaining unchanged. The dependent variable is an index variable (0/1/2 if the price has remained unchanged/decreased/increased, respectively). Controls are *Previous 9-ending* (1 if the pre-change price was 9-ending), *Price level* (price without the penny digit), dummies for *product categories* and for *districts*.

*** $p < 0.01$. Robust standard errors, clustered at the product category level, are reported in parentheses.

However, we shall note that unlike the Dominick's data, where we have a single retailer, with a single store format, carrying 29 product categories, and operating in the same area, the Israeli data covers multiple chains, in multiple store formats (supermarkets and drugstores), covering 99 product categories, and operating in different parts of Israel. This variation introduces considerable heterogeneity in the Israeli data.

To test whether or not 9-ending prices are more rigid upward than downward, therefore, we need to control for this heterogeneity in the data. We estimate a multinomial-logit regression model of the probability that a 9-ending price will increase, decrease or remain unchanged, as in regression Eq. (4). Similar to Section 3.3.3, the dependent variable is an index variable, which equals 0/1/2 if the price has remained unchanged/decreased/increased, respectively. The main control variable is *previous-9-ending* (1 if the price in the previous month was 9-ending).²³ The model estimation results are reported in Table 9.

The coefficient estimates of *previous-9-ending* are both negative, suggesting that 9-ending prices are more rigid than other prices. However, they are more rigid upward ($\beta_2 = -0.34$, $p < 0.01$) than downward ($\beta_1 = -0.28$, $p < 0.01$). The difference is statistically significant ($\chi^2 = 3.8$, $p < 0.05$). Thus, once we control for the heterogeneity in the data, we find that in the Israeli retail price data, like in the U.S. retail price data, the rigidity of 9-ending prices is asymmetric.

Setting all variables equal to their average values and setting all the dummies equal to zero, we find that compared to a non 9-ending price, a 9-ending reduces the likelihood of a price increase from 19.9% to 15.5%, a reduction of 22.4%. In contrast, compared to a non 9-ending price, a 9-ending reduces the likelihood of a price decrease from 10.3% to 8.5%, a reduction of 17.6%. As in the US, therefore, the effect of 9-endings is larger on price increases than on price decreases.

3.4.4. Asymmetry in the size of price changes

Next, we test the differences between the size of price increases and price decreases when a price is 9-ending. As expected, the average increase of a 9-ending price, 28.2%, exceeds the average decrease, 20.0% ($t = -28.4$, $p < 0.01$). As a formal test, we estimate the regression model in Eq. (5), where the dependent variable is the absolute value of the percentage price change. As the independent variables, the regression includes *previous-9-ending* and its interaction with *price decrease*, *price-level*, and dummies for *product categories* and for *districts*.

²³ The matrix of controls X includes *price level*, and dummies for *product categories*, and for the *districts*.

Table 10

The size of 9-ending price change – Israeli supermarkets and drugstores.

Previous 9-Ending	0.05 (0.008)***
Previous 9-Ending × Price-Decrease	−0.09 (0.015)***
Price level	0.0007 (0.0001)***
Constant	0.06 (0.007)***
R ²	0.04
N	59,855

The table reports estimation results of a linear regression of the percentage price change, conditional on price change (average = 0.22). Controls are *Previous 9-ending* (1 if the pre-change price was 9-ending), *Price-decrease* (1 if the price change is negative), *Price level* (price without the penny digit), and dummies for product categories and for districts.

*** $p < 0.01$. Robust standard errors, clustered at the product category level, are reported in parentheses.

The estimation results, reported in Table 10, suggest that when 9-ending prices increase, they increase by 5% more than the expected change in non 9-ending prices. The interaction of 9-ending with price decrease is negative ($\beta = -0.09$, $p < 0.01$). Thus, when 9-ending prices decrease, they decrease by 9% less than the expected change in other prices. The results are, therefore, similar to the results we obtained for the Dominick's data: The expected increase in a 9-ending price is $5\% + 9\% = 14\%$ larger than the expected decrease in a 9-ending price. The difference is statistically significant ($F = 7.7$, $p < 0.01$).

3.4.5. 9-ending price increases and consumer inattention

As in the case of Dominick's, we next explore the link between the size of price increases and 9-endings, to assess the possibility that people are inattentive to increases in 9-ending prices because these tend to be small. In the Israeli data, the descriptive statistics provide conflicting evidence: The average absolute (percentage) price increase, NIS3.3 (26.4%), is smaller (larger) when the new price is 9-ending than when the new price is not 9-ending, NIS4.4 (21.8%). The differences are statistically significant at 1%: for absolute price increases, $t = 4.2$, and for % price increases, $t = 5.2$.

Therefore, to formally assess whether or not 9-ending price increases are smaller than the increases of prices with other endings, we estimate regression Eq. (6). The dependent variable, *price-increase*_{ijt}, is the price-increase of a good *i* in store *j* in week *t*. The main independent variable is *9-ending*, which equals 1 if the price is 9-ending and 0 otherwise.²⁴ We estimate this regression twice. In the first, *price-increase* is measured in absolute terms (in NIS). In the second regression, *price increase* is measured in relative terms (in percent).

The estimation results (reported in Table 15B in Online Appendix T) indicate that in the regression of absolute price increases, the coefficient estimate is positive, although not statistically significant ($\beta = 0.31$, $p > 0.10$). In the regression of relative price increases, the coefficient estimate is negative but statistically not significant ($\beta = -0.01$, $p > 0.10$).

Therefore, the results for the Israeli data suggest that there is no difference between the price increase when the new price (the price following the increase) is set at a 9-ending, and when the new price is set at some other ending. Thus, in Israel as in the U.S., consumers do not have less incentive to pay attention to increases in 9-ending prices, in comparison to other prices.

4. Robustness

We run numerous robustness tests and analyses, which are discussed in detail in online appendices as follows. (1) We check if the results we report in Table 1 are robust to dropping most of the controls and leaving only the 9-ending and 0-ending dummies, and their interactions with the dummy for the price-comparison treatments (Appendix W). (2) We check if the results we report in Tables 1 and 2 are robust to different estimation strategies. For that purpose, we estimated all the regressions discussed in Sections 3.1.2 and 3.1.3 again using (a) fixed effects, (b) pooled OLS, and (c) probit. The results of these analyses are presented and discussed in Appendix J and Appendix K, respectively. (3) We check if the results we report for Dominick's transaction prices also hold for regular prices. Note that in Dominick's data, 9-endings are more likely to be regular prices than sale prices, as the figures in Table 14A in Appendix O indicate. It is possible, therefore, that the asymmetric rigidity of 9-ending prices that we are documenting, is primarily driven by 9-ending regular prices going down to non 9-ending sale prices. To control for this possibility, we repeated all the tests and analyses after excluding the sale prices and their bounce-backs to regular prices. To identify the sale prices, we used the Dominick's sales indicator variable, which is included in the Dominick's dataset. These results are discussed in Appendices L–N. (4) In Appendices M and N, we also test whether the results are robust to the inclusion of outlier observations of the wholesale prices.²⁵ (5) We check whether our results are driven by inflation, since Chakraborty et al. (2015) find that retailers try to camouflage price increases during inflationary periods. This might be relevant in our case because during the sample period covered by

²⁴ The matrix of controls *X* includes dummies for the year and for the product categories.

²⁵ We repeat these analysis using probit models to estimate equations (3)–(5). See Online Appendices E and F.

the Dominick's data (i.e., 1989–1997), the U.S. experienced a moderate inflation, with an annual inflation rate between 5% (the first year of the sample) and 2.5% (the last year of the sample). These results are discussed in Appendices D and V. (6) It is well-known that Dominick's sale indicator variable is incomplete (Peltzman, 2000, Dominick's User Manual 2013). As a further test, therefore, we repeat (3)–(5) again, but this time using the sale filter of Nakamura and Steinsson (2008, 2011). Following their algorithm, we categorize a price as a sale price if the price first decreases, stays at the low level for up to four weeks, and then bounces back to a price that is equal or higher than the pre-sale price. The results of these estimations are reported in a series of tables and accompanying discussions, in Appendix D,²⁶ and in Appendices L–N. (7) There is also a possibility that our results for the Dominick's data are affected by the removal of the end-points, and by missing observations. We therefore interpolate the missing price observations in the Dominick's data using the preceding values, i.e., we set a price missing in week t to equal its value in week $t-1$. This expands the dataset from 81,982,683 to 94,695,300 observations. The results of the estimations using the expanded (i.e., interpolated) dataset are reported in Appendix D. Additional robustness tests using Dominick's data include: (8) An analysis of the probability of a change in the right-most digit (Appendix G). (9) A comparison of the levels of 9-ending and non 9-ending prices (Appendix H). (10) A test of whether or not non 9-ending prices also exhibit asymmetric rigidity (Appendix U). Finally, (11) we also assess the possibility that the results for the Israeli CPI data are affected by inflation, or by possible changes in the pricing strategy over time, which we capture by adding a linear time trend to the regression (Appendix I). (12) In Appendices I, P, R and S, we examine whether the results for the Israeli supermarkets and drugstores also hold for regular prices using a sale filter of Nakamura and Steinsson (2008, 2011). (13) Using the field study data, we study the consumers' recall of price changes by analyzing the probability of responding that the price has decreased or increased relative to responding that it has remained unchanged (Appendix C). The findings we report in all these appendices are all consistent with the results reported in the paper.²⁷

5. Conclusions and implications for macroeconomics

We document asymmetric adjustment of 9-ending prices using four datasets. In two different retail price datasets (one from the U.S. and another from Israel), we find that 9-ending prices are more rigid upward but not downward, in comparison to non 9-ending prices. The lab experiment and the field data suggest that the asymmetry is due to consumers' use of 9-endings as a signal for low prices. Retailers seem to take advantage of the consumers' heuristic processing of 9-ending price information, by strategically keeping prices at 9-endings more often after price increases than after price decreases, leading to the asymmetric rigidity of 9-ending prices.

This finding is important for several reasons. First, 9-ending is a dominant feature of many retail prices, a fact that has been mostly ignored by macroeconomists until very recently. In our data, 62–65% of the prices end with 9. Some studies report even higher figures. Anderson et al. (2015), for example, find that over 95% of the prices in their data are 9-ending. Moreover, Levy et al. (2011) show that 9 is the most frequent ending at the penny, dime, dollar and ten-dollar digits in the traditional retail price data, as well as in the internet price data they study.

Second, studies using micro-level data report that 9-ending prices are far more rigid than other prices, which should be of interest to macroeconomists in light of the prevalence of the 9-ending prices. With the exception of Kashyap (1995) and Blinder et al. (1998), however, much of the sticky price literature ignores this by relying almost exclusively on menu cost to generate price rigidity. Indeed, recent studies note the importance of the rigidity of 9-ending prices. Knotek (2011) and Anderson et al. (2015), for example, call for greater attention of macroeconomists to 9-ending prices.

Third, the asymmetry we document is interesting because it is opposite to the standard Keynesian asymmetry, which is usually characterized by “prices that are sticky downward but not upward” (Ball et al., 1988, p. 12). We report the exact opposite: we find that 9-ending prices are more rigid upward than downward, which is surprising and worthy of our attention.

Fourth, our findings add to the growing literature on strategic retail pricing and its effects on inflation. For example, Chakraborty et al. (2015) study pricing at British supermarkets and find that while basket prices rose, many individual prices fell. The frequent small price cuts, they conclude, “were used to disguise the basket price increases” (p. 71). Using data for a US retailer, Anderson et al. (2017) find that discounts increase when regular prices increase in response to a wholesale price increase. They conclude that the retailer is “trying to mask the associated regular price increase” (p. 3). Thus, in these studies, the retailers deliberately disguise their basket price increases by frequent sales and small price cuts, as to not antagonize customers (Rotemberg, 2005; Blinder et al., 1998).²⁸ The retailers we study also seem to follow a strategy of “hiding” price increases, but they choose to adopt a different tactic. They use 9-endings to mask price increases by taking advantage of consumers' mental and cognitive constraints that limit their ability to fully process price and price

²⁶ In these analyses, we use a probit regression model for estimating regression equations (3)–(5).

²⁷ Consider the following observation: in the 90 tables we present (80 in Online Appendices, 10 in the paper), only two coefficients are inconsistent with our predictions. These are the coefficients of the interaction term of 9-ending dummy and price decrease, in Tables 6a' and 6a'', both in Online Appendix D.

²⁸ Frequent small price decreases to conceal overall basket price hike that Chakraborty et al (2015) find, seems counter to the evidence of Chen et al (2008) who find frequent small price increases, which they explain by consumer inattention to small price changes. Using a game theoretic model, Chakraborty et al (2015) show that both strategies (“many small price cuts with few large price hikes,” and “many small price hikes with few large price cuts”) are Nash equilibria, and thus theoretically possible.

change information, and their tendency to interpret 9-ending prices as low prices. The outcome, however, is similar: there are discrepancies between the price changes as perceived by consumers and the actual price changes implemented by the retailers.²⁹

The work ahead is challenging, particularly on the theory front. As far as we know, Knotek (2016) is the only study that considers theoretically the macroeconomic implications of 9-ending prices. He shows that in a model that contains both menu cost and 9-ending prices, menu cost plays a marginal role as a source of price rigidity, once the profit benefit of 9-ending prices is allowed, which is significant because menu cost has been the leading explanation for price rigidity (Anderson et al., 2015). He finds that the model generates movements in output distinct from those of the simple menu cost model. In light of these findings, the asymmetry in the rigidity of 9-ending prices that we document can potentially have macroeconomic significance.³⁰

The existing empirical evidence (e.g., Cover, 1992) suggests that expansionary monetary policy has a stronger impact than a contractionary monetary policy, which can be explained by the traditional downward price rigidity (e.g., De Long and Summers, 1988, Ball and Mankiw, 1994). Our findings suggest that in a model that incorporates 9-ending prices with asymmetric rigidity, this Keynesian type asymmetric effect of monetary policy will likely be weaker (if not reversed), because the asymmetry we are documenting here is in the opposite direction.

Future work should therefore explore ways of incorporating 9-ending price phenomenon in macroeconomic/monetary economy models, by constructing dynamic stochastic general equilibrium models that incorporate structural motives for the optimality of 9-ending prices. This is challenging since our findings suggest that consumers use 9-ending as a heuristic for low prices.³¹ Whatever the motive for the use of 9-endings, however, the finding that 9-endings affect consumers' price perceptions by lulling them into thinking that 9-ending prices are lower than they actually are, can lead to kinks or discontinuities in the demand function, which would be present in the firm's profit function as well.³²

Besides confronting the resulting technical challenges, such models would have to confront the stylized facts of Klenow and Malin (2011) and others, as well as some of the facts that we are documenting here about the asymmetric rigidity of 9-ending prices. These models, when available, will enable us to assess the aggregate dynamics that 9-ending prices might generate, and consequently, help us understand the implications of the rigidities and the asymmetries that 9-ending prices generate, for monetary policy and for macroeconomics.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2019.01.005.

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²⁹ These findings are in line with the key point of Akerlof and Shiller (2015, pp. vii, 1): "...our free-market system tends to spawn manipulation and deception...if we have some weakness...in the phishing equilibrium someone will take advantage of it." 9-ending pricing can be a fooling-equilibrium where consumers rely on 9-endings as a signal for low prices and retailers respond by setting/keeping 9-endings after price increases. Retailers gain because this enables them to conceal price increases while shoppers gain by saving the costs of cognitive efforts ("thinking costs," Shugan 1980) needed for noticing and assessing price changes.

³⁰ Knotek's model, however, is set in a partial equilibrium framework, where revenues or demand have no structural role. In addition, he does not model or derive optimal price setting policy, etc. His model is also agnostic about the reason for the use of 9-ending prices, and thus the model does not explain why retailers choose 9-ending pricing.

³¹ Other explanations for the use of 9-ending prices also rest on some form of heuristics. For example consumers might truncate the last digit or round prices up or down, etc. (Schindler and Kirby 1997, Schindler 2001, 2006, Stiving and Winer 1997, Stiving 2000, Monroe and Lee 1999). Basu (1997) is an exception: he shows that 9-ending prices can be a rational expectations equilibrium.

³² The overrepresentation of 9-ending prices cannot be the outcome of Benford law, which argues that in naturally occurring data, the distribution of left-most-digits (LMD) is logarithmic, not uniform (Varian 1972). For example, the $p(\text{LMD} = 1) = \log 2 = 0.3$, $p(\text{LMD} = 2) = \log 3/2 = 0.17$, etc. This was discovered by Newcomb (1881), who noticed that in public libraries, the pages of logarithm tables containing numbers starting with 1 were more worn out than other pages. Benford (1938) confirmed these findings. Under the Benford law, the probability of digits approaches uniform distribution as we move from left to right. For the second left-most digits the skew is from 12% for 0, down to 8.5% for 9. Nigrini (2002) shows that the last 2-digits are equally likely for each combination from 00 to 99 in 3-digit and higher numbers. Benford law, thus, cannot explain the phenomenon of 9-ending prices.

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